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Developing a Tool to Support Decisions on Patient Prioritization at Admission to Home Health Care

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Abstract

Background and aims: Millions of Americans are discharged from hospitals to home health every year and about third of them return to hospitals. A significant number of rehospitalizations (up to 60%) happen within the first two weeks of services. Early targeted allocation of services for patients who need them the most, have the potential to decrease readmissions. Unfortunately, there is only fragmented evidence on factors that should be used to identify high-risk patients in home health. This dissertation study aimed to (1) identify factors associated with priority for the first home health nursing visit and (2) to construct and validate a decision support tool for patient prioritization. I recruited a geographically diverse convenience sample of nurses with expertise in care transitions and care coordination to identify factors supporting home health care prioritization. Methods: This was a predictive study of home health visit priority decisions made by 20 nurses for 519 older adults referred to home health. Variables included sociodemographics, diagnosis, comorbid conditions, adverse events, medications, hospitalization in last 6 months, length of stay, learning ability, self-rated health, depression, functional status, living arrangement, caregiver availability and ability and first home health visit priority decision. A combination of data mining and logistic regression models was used to construct and validate the final model. Results: The final model identified five factors associated with first home health visit priority. A cutpoint for decisions on low/medium versus high priority was derived with a sensitivity of 80% and specificity of 57.9%, area under receiver operator curve (ROC) 75.9%. Nurses were more likely to prioritize patients who had wounds (odds ratio [OR]=1.88), comorbid condition of depression (OR=1.73), limitation in current toileting status (OR= 2.02), higher numbers of medications (increase in OR for each medication =1.04) and comorbid conditions (increase in OR for each condition =1.04). Discussion: This dissertation study developed one of the first clinical decision support tools for home health, the "PREVENT"- Priority for Home Health Visit Tool. Further work is needed to increase the specificity and generalizability of the tool and to test its effects on patient outcomes.

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DEVELOPING A TOOL TO SUPPORT DECISIONS ON PATIENT PRIORITIZATION AT ADMISSION TO HOME HEALTH CARE.

Maxim Topaz

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DEVELOPING A TOOL TO SUPPORT DECISIONS ON PATIENT PRIORITIZATION AT ADMISSION TO HOME HEALTH CARE.

DEDICATION

To my family, Leah and Abbigail ~

All my love and sincerest gratitude for seeing me through this accomplishment

To my parents, Michail and Natalia ~

Who introduced me to this world and guided my path

To my grandparents, Nadejda, Peter, Doba and Gregorij ~

Whose life stories at the times of great turmoil determined who I am

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ABSTRACT

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Background and aims: Millions of Americans are discharged from hospitals to home health every year and about third of them return to hospitals. A significant number of rehospitalizations (up to 60%) happen within the first two weeks of services. Early targeted allocation of services for patients who need them the most, have the potential to decrease readmissions. Unfortunately, there is only fragmented evidence on factors that should be used to identify high-risk patients in home health. This dissertation study aimed to (1) identify factors associated with priority for the first home health nursing visit and (2) to construct and validate a decision support tool for patient prioritization. I recruited a geographically diverse convenience sample of nurses with expertise in care transitions and care coordination to identify factors supporting home health care prioritization. **Methods**: This was a predictive study of home health visit priority decisions made by 20 nurses for 519 older adults referred to home health. Variables included sociodemographics, diagnosis, comorbid conditions, adverse events, medications, hospitalization in last 6 months, length of stay, learning ability, self-rated health, depression, functional status, living arrangement, caregiver availability and ability and first home health visit priority decision. A combination of data mining and logistic regression models was used to construct and validate the final model. **Results**: The final model identified five factors associated with first home health visit priority. A cutpoint for decisions on low/medium versus high priority was derived with a sensitivity of 80% and specificity of 57.9%, area under receiver operator curve (ROC) 75.9%. Nurses were more likely to prioritize patients who had wounds (odds ratio [OR]=1.88), comorbid condition of depression (OR=1.73), limitation in current toileting status (OR= 2.02), higher numbers of medications (increase in OR for each medication =1.04) and comorbid conditions (increase in OR for each condition =1.04). **Discussion**: This dissertation study developed one of the first clinical decision support tools for home health, the “PREVENT”- Priority for Home Health Visit Tool. Further work is needed to increase the specificity and generalizability of the tool and to test its effects on patient outcomes.

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CHAPTER 1: INTRODUCTION

Each year nursing administrators and intake nurses of approximately 12,000 home health agencies across the United States (US) are deciding on and prioritizing health resource allocation for more than 11 million older patients admitted to their agencies (The National Association for Home Care & Hospice, 2010). Yet, there are no national, empirically derived standards to assist in making these important decisions. Increasing severity of patients' health status (Murtaugh et al., 2009) and high hospital rehospitalization rates (Jencks, Williams, & Coleman, 2009) further increase the complexity and the importance of an effective home health admission processes.

Nationwide evidence shows that about 30% of those admitted to home health services are hospitalized during the home health episode (Center for Medicare and Medicaid Services, 2013a; MedPac, 2014). There is a growing body of evidence showing that at least some of these admissions may be prevented by a timely and appropriate targeted allocation of healthcare resources (Centers for Medicare & Medicaid Services, 2002; Fortinsky, Madigan, Sheehan, Tullai-McGuinness, & Fenster, 2006; Markley, Sabharwal, Wang, Bigbee, & Whitmire, 2012; McDonald, King, Moodie, & Feldman, 2008).

Population of Interest: Patients Discharged From Hospitals

Among the adult population admitted to home health agencies, those discharged from hospitals are the most vulnerable. In addition to complex medical conditions, many hospitalized patients experience lack of sleep, inappropriate caloric intake and high levels of stress during their hospital stay (Dupertuis et al., 2003; Friese, 2008; Singh, Watt, Veitch, Cantor, & Duerksen, 2006; Young, Bourgeois, Hilty, & Hardin, 2008).

Krumholtz (2013) suggested that these patients often develop a Post-Hospital Syndrome- an acquired, transient condition that puts them at a great risk for poor health outcomes (such as rehospitalization or drug adverse events). These patients are at a greater risk for rehospitalization than the general population of home health patients. In fact, up to 34% of patients discharged from hospitals to home health are rehospitalized within 30 days and 40-60% percent of these readmissions occur within the first two weeks (Anderson, Clarke, Helms, & Foreman, 2005; Berry et al., 2011; Bowles, 2012; Markley, Sabharwal, Wang, Bigbee, & Whitmire, 2012; C. Murtaugh, 2013; O'Connor, Hanlon, & Bowles, 2014). Similarly, data from Philadelphia shows that almost 30% of recently hospitalized patients who were discharged from the hospital and started receiving home health services were rehospitalized, with half of all rehospitalizations of this group occurring in the first 14 days post hospital discharge. (Bowles, 2012). This vulnerable population of patients discharged from hospitals is the focus of the current study.

The Problem: Identifying Appropriate Timing for the First Home Health Visit

The first home health visit (usually by a Registered Nurse) is one of the most important steps of the home health episode. During this visit, the initial patient assessment is conducted and unique care plan is created according to the patients' needs and problems. Currently, the Center for Medicare and Medicaid Services (CMS) requires that all patients admitted to home health services receive an initial assessment within the first 48 hours of their hospital discharge or referral to home health (Centers for Medicare & Medicaid Services, 2012a). However, no empirical evidence supports this arbitrarily chosen time period. For today's home health agencies serving patients of diverse clinical complexity (ranging from patients who require custodial care type assistance in the activities of daily living to patients who are ventilator dependent), identifying appropriate timing of the first visit is crucial, especially for patients with urgent healthcare needs. According to the CMS, home health agencies fail to see 11% (SD 10.7%) of their patients within 48 hours; other anecdotal reports suggest that these numbers might be even greater.

Effects of Inappropriate Patient Prioritization

Many patients discharged from hospitals are not ready for discharge (up to 60% of all discharged patients according to some reports) for a variety of reasons, including lack of knowledge on how to deal with the complex medical regimens and new self-care activities (Barnason, Zimmerman, Nieveen, Schulz, & Young, 2012; Bobay, Jerofke, Weiss, & Yakusheva, 2010; Coffey & McCarthy, 2012; Foust, Vuckovic, & Henriquez, 2012; M. Weiss, Yakusheva, & Bobay, 2010). A typical home health patient suffers from at least four complex medical conditions (Caffrey, Sengupta, Moss, Harris-Kojetin, & Valverde, 2011) and takes about eight medications (McDonald et al., 2012). However, many patients do not visit their primary care providers for the follow up visits within the first 60 days of hospital discharge for a variety of reasons such as patient treatment non-adherence (Alper, O'Malley, & Greenwald, 2013; Grafft et al., 2010; Hernandez et al., 2010; Jencks et al., 2009; Misky, Wald, & Coleman, 2010; Sharma, Kuo, Freeman, Zhang, & Goodwin, 2010; Zisberg et al., 2011). This combination of high clinical complexity, poor discharge readiness and poor follow-up by primary care providers makes home health patients vulnerable to poor care outcomes. For these patients, identifying appropriate timing of the first nursing visit is critical to avoid rehospitalizations and other negative outcomes.

Remarkable variability is also seen in publically reported CMS outcomes. The severity of illness and age adjusted number of hospital admissions from home health agencies in the US varies between 2% and 87% (SD=10) (Centers for Medicare & Medicaid Services, 2012a). In addition, some geographic areas and providers are outliers in terms of rehospitalizations: for example, agencies at the 25th percentile of rehospitalizations have a rate of 25%, compared with 39% for agencies at the 75th percentile (MedPac, 2014). This variability indicates that at least some home health patients are not getting appropriate care at the right time because of the differing admission processes and possibly inappropriate prioritization.

To date, no US studies focus directly on factors related to patients' urgent and non-urgent needs and conditions at the admission to home health services. Moreover, it is not clear what disease characteristics, medications, patient needs, social support characteristics and other factors are contributing to the important decisions regarding priority for the first home health visit for millions of patients admitted to home health agencies from acute care settings every year.

Study Purpose and Specific Aims

The long term goal of this investigator is to build a research trajectory focusing on providing optimal and timely evidence-based care in home health settings. The primary purposes of this study were: 1) to capture the knowledge of home health experts on factors affecting home health admission decisions, and 2) to use this knowledge to build and validate a decision support tool to assist home health managers and intake nurses in prioritizing patients for the first home health visit. The specific aims of the study were:

Aim 1) To identify disease characteristics, medications, patient needs, social support characteristics, and other factors identified by experts as associated with

patient's priority for the first home health nursing visit (see Table 1 for the complete list of study variables)**.**

Aim 2) To construct and validate the best predictive model imitating experts' decisions on patient's priority for the first home health nursing visit.

The use of a decision support tool suggesting priority for the first nursing visit may have significant clinical implications. First, this study results may contribute to improving the quality and consistency of patient-centered care planning decisions during the transition from hospital to home. Clinicians could use this tool to prioritize the scarce available resources. For instance, our results might assist clinicians in identifying high risk candidates for interventions such as close home based monitoring (telehealth). The goals of this dissertation are also consistent with recent legislative trends in the US healthcare requiring tools for better coordinated and personalized care (e.g. the Healthcare Reform (U.S. Department of Health & Human Services, 2012)).

Definition of Key Terms

<u>Home health services</u>: comprehensive medically necessary services provided by a recognized provider to a patient in the home.

<u>Home health agency</u>: an organization that provides home health services.

<u>Hospital discharge</u>: the process in which a patient is released from the hospital by health care professionals.

<u>Home health agency admission</u>: a structured process of patient intake to receive home health services that usually culminates with a first nursing visit.

<u>Time span of the hospital to home health agency admission</u>: the home health service admission starts with physician referral, usually around the time of hospital discharge. A

home health service admission is complete when first nursing visit is conducted by home health agency representative (registered nurse in most of the cases).

CHAPTER2: BACKGROUND AND REVIEW OF LITERATURE

Theoretical Framework

Two theoretical frameworks guide this study. First, the transitions theory suggested by Meleis (Im, 2009; A. Meleis, 2010; Meleis, Sawyer, Im, Messias, & Schumacher, 2000) is used as a lens to systematically examine the process of an individual's transition from hospital to home health settings. Transition theory is used to support Aim 1 of this study. Secondly, the Data-Information-Knowledge-Wisdom (DIKW) framework (American Nurses Association, 2008; Matney, Brewster, Sward, Cloyes, & Staggers, 2011) guides the conceptualization of the proposed tool (for patient prioritization at the admission to home health) in a broader healthcare informatics domain. The DIKW framework supports Aim 2 of the proposed study by offering a general description of the steps involved in constructing tools for clinical decision support.

Transitions theory

Transitions theory emerged in the late 1970s and since then, it was constantly developed and refined by Meleis and many others (Im, 2009; Im, 2011; A. Meleis, 2010; Schumacher & Meleis, 1994). In general, transitions can be defined as a passage from one state to another, a process triggered by change. Because nursing practice and research frequently address various types of transitions (e.g. immigration transition, health-illness transition, administrative transition, etc.), transitions theory has been easily adopted and welcomed in nursing research, education, and practice (Im, 2011; Meleis et al., 2000). Nurses are often the primary caregivers of clients and their families who are undergoing transition and transitions theory can provide a lens through which nursing phenomena related to transitions can be systematically and comprehensively viewed (Im, 2011; Meleis, 2010). Others have successfully applied transitions theory to analyze the process of patient discharge from hospital to home (Coffey & McCarthy, 2012; Coffey, 2012).

The transitions theory includes six central components: types and patterns of transitions; properties of transition experiences; transition conditions: facilitators and inhibitors; process indicators; outcome indicators; and nursing therapeutics (see Figure 1). In this study, I focus on two central populations; hospitalized patients (and their families) and nurses.

Types and Patterns of Transitions

The first component of the framework describes types and patterns of transitions. Transitions are classified into **four major types**: health/illness, situational, developmental, and organizational (Meleis et al., 2000). Meleis and colleagues (2000) suggested that researchers have to consider the patterns of all significant transitions in a particular situation rather than focusing on only one specific type of transition.

For the majority of patients, admission to a hospital is a major health/illness transition. This type of transition includes sudden or gradual role change (resulting from moving from wellness to acute or chronic illness or vice versa). For example, the most common reasons for hospitalization in the US are newly diagnosed health conditions (such as heart failure [HF]) or exacerbation of a chronic disease (such as chronic obstructive pulmonary disease [COPD]) (Foltz-Grey, 2012). Similarly, the majority of patients admitted to home health suffer from diseases of the circulatory system (mostly HF) or endocrine, nutritional, and metabolic diseases (predominantly diabetes mellitus) (The National Association for Home Care & Hospice, 2010). This evidence supports the assumption that a majority of patients receiving home health are undergoing a major health/illness transition.

Another central type of transition for patients admitted to home health is a situational transition. These transitions include an addition or subtraction of persons in a preexisting constellation of roles. Examples of such transitions include new parenthood, widowhood or immigration (Meleis, 2010). Because of Center for Medicare and Medicaid (CMS) regulations, a vast majority of patients transitioning from hospital to home health are homebound, i.e. “have a condition, due to an illness or injury, that restricts the ability of the individual to leave his or her home except with the assistance of another individual or the aid of a supportive devise (such as crutches, a cane, a wheelchair or a walker), or if the individual has a condition such that leaving his or her home is medically contraindicated” (Center for Medicare and Medicaid Services, 2011a). New or recurring family caregiving is often a major situational transition for homebound patients and their families; this situation not only involves a major shift in personal and interpersonal conceptions but also frequently requires an active involvement of significant others (e.g. children or relatives) (Meleis, 2010). These transitions might cause conflicts if they are unanticipated or unrecognized (e.g. requiring a full time working daughter to move in to her elderly mother’s house to assist her to recover after hip fracture). **In this study, the amount and type of family caregiving is presented in comprehensive patient case summaries.**

Additional type of transitions are developmental transitions; role transitions that are encountered in the normal course of growth and development. In this study, the major developmental transition is a transition from adulthood to old age. This type of transition is often accompanied by gerontologic issues relating to identity, retirement and chronic illness (Meleis, 2010; Tornstam, 2005; Tornstam, 2010). Developmental changes undergone by the home health patient and by a significant other should be considered by the healthcare team to provide patient and family centered care. One particular example of such transition is widowhood that is experienced by many of the older individuals.

The fourth type of transition is the organizational transition. Thus far, the types of transitions presented focused on individuals and their families while organizational transitions represent transitions in the environment. These transitions are often precipitated by changes in the wider social, political or economic environments or by changes in structure or dynamics with organizations (Meleis, 2010; Meleis et al., 2000). There are two central applications of organizational transitions for this study. First, the political and financial healthcare environments of the US healthcare are changing; the American Recovery and Reinvestment Act of 2009 (Office of Management and Budget Guidance to Federal Agencies, 2009) and the advent of Healthcare reform (U.S. Department of Health & Human Services, 2012) have created strong incentives for care coordination, technology adoption and community care. Some of these changes are already widely implemented (such as the adoption of electronic healthcare records (Health Information Management Systems Society, 2012) and some are coming (e.g. bundled payments for healthcare services). Medicare has also started to financially penalize institutions for rehospitalizations caused by certain conditions (e.g. HF, pneumonia), which affects organizational behaviors. These organizational transitions create the context for the present study.

The second component of the transitions theory is the **transition pattern**. Each of the aforementioned transitions might be single, multiple, sequential or simultaneous. Also, transitions might be related or non-related. For example, an older woman might be admitted to home health from the hospital because of a recurrent hospitalization caused by an exacerbation of HF (sequential health/illness transition). At the same time, her full time working daughter is now required to help her homebound mother with regular activities on a daily basis (simultaneous situational transition). Also, patients present in the study sample might experience unexpected transitions patterns, such as emergency admission or unexpected hospital discharge. Thus, examining each transition pattern is an important consideration for the proposed study. **The transition pattern was approximated by patient characteristics (e.g. prior activities of daily living status) and caregiver characteristics (e.g. availability, days and times at which caregiver is available and caregiver's willingness to help)**. Additional factors that indicated the pattern of a transition in this study were **the length of hospital stay and type of admission (emergency versus elective)**.

Properties of a Transition Experience

The following properties are common to a majority of transitions: awareness; engagement; change and difference; time span; and critical points and events (Im, 2009; Im, 2011; Meleis, 2010). Transitions' properties are complex and interrelated rather than discrete.

<u>Transition awareness</u> relates to perception, knowledge, and recognition of a transition experience. Levels of awareness vary among individuals; these levels depend on socio-economic background, knowledge and other factors. For example, in our recent study examining self-care decisions of patients with heart failure, we found that situation awareness (e.g. personal recognition of symptoms of shortness of breath) was essential to initiate subsequent self-care steps (such as taking a diuretic to decrease fluid overload) (Riegel, Dickson, & Topaz, 2012). Awareness is also an important component of nursing care; without being aware of a patient's symptoms, the nurse would not provide the required care. One of the goals of this study is to increase nurses' awareness to the most pressing clinical and social issues at admission to a home health setting that can be expected to subsequently influence outcomes. Explicit identification

of these critical factors will help nurses to prioritize patients with the most acute needs, which if addressed, can help avoid unnecessary hospital admissions or other negative outcomes.

Transition engagement is defined as the degree to which a person demonstrates involvement in the processes inherent in the transition. Examples of engagement include looking for information, actively preparing, and proactively modifying activities (Meleis, 2010). Engagement is somewhat contingent on the levels of awareness; without awareness that one is in a transition, it is unlikely that the individual will actively engage in the situation. **In the current study, patients' engagement and awareness were approximated by several variables.** For example, a variable presenting patient's barriers to follow medication schedule indicated the level of a patient's ability to engage with a transition to home (response options include, among others, the "Inability to prepare and administer dose correctly" or "Lack of knowledge regarding medication purpose").

Change and difference are essential properties of transitions. For example, newly prescribed insulin injections for an elderly individual admitted to home health is a critical change during a health/illness transition of newly diagnosed diabetes mellitus. Confronting difference is often exemplified by unmet or divergent expectations, feeling different, or seeing the world and others in different ways (Meleis, 2010). For individuals admitted to a home health agency, unmet expectations might be those of increased caregiving by family members, such as a grandson caregiving for his grandmother with heart failure. In practice, the grandson might be reluctant or unwilling to take care of the homebound grandparent. **In this study, change and difference property were approximated by a set of variables, such as caregiver ability and willingness to help or change in patient functional status.**

Time span: all transitions are characterized by flow and movement over time. Some researchers characterized transitions as having an identifiable time span and end points while others argued that it is limiting and counterproductive to put strict boundaries around the transition of interest (Meleis, 2010; Meleis et al., 2000). **Factors associated with patient's priority between hospital discharge and first nursing home health visit were examined in this study.**

The last property of a transition experience is the critical points and events. Some transitions are associated with a marker event; such as birth, death, or the cessation of menstruation, while in other transitions specific marker events are not as evident (Meleis, 2010). Research based on the transitions theory validates that critical points or events are often associated with a period of uncertainty marked with fluctuation, continuous change, and disruption in reality (Meleis, 2010). Also, each critical point requires the nurse's attention, knowledge, and experience in different ways. In the proposed study there are several critical points, the most important being the first home health nurse visit. The other critical event is the discharge from the hospital.

Transition conditions: facilitators and inhibitors

In nursing, humans are defined as active beings constructing meanings around health transitions. In order to understand transitions, it is necessary to uncover the personal, community, and societal conditions that facilitate or hinder progress toward achieving a healthy transition (Meleis, 2010).

Personal conditions include meanings that patients and their social groups attribute to the transitions; these meanings might facilitate or hinder healthy transition. Transitions also affected and affect the cultural beliefs and attitudes. In the proposed study, certain patient populations could be stigmatized, which might lead to decreased levels of social support when experiencing hospital-home health transitions. For example, it was found that patients with mental health problems might experience more pressure and less social support during inter-setting transitions (Jones et al., 2009). Similarly, socio economic status might serve as an inhibitor or facilitator of an optimal transition; it is well documented that economic disparities exist in home health (Davitt, 2012) and other outpatient (Liao et al., 2011) and inpatient settings (Hellander & Bhargavan, 2012).

Community conditions also facilitate or inhibit health transitions. In the proposed study, some of the possible community level factors facilitating hospital-home health transitions were living with or close to the informal caregiver (e.g. family member) or safe home environment (O'Connor, 2012). Examples of transitions facilitators and inhibitors are presented in the Figure 1.

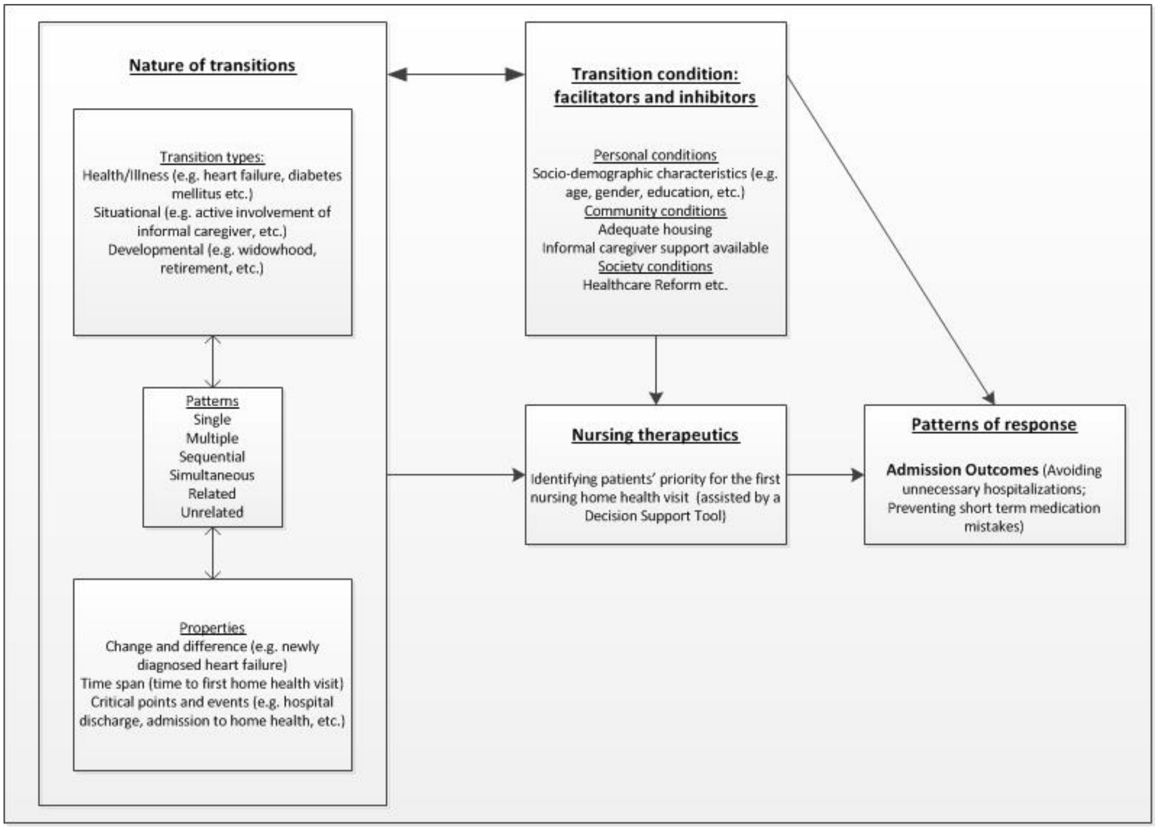
Patterns of Response

Meleis (2010) suggested that nursing is concerned with process and outcome indicators of health transitions; identifying process indicators that move clients either in the direction of health or toward vulnerability and risk allows early assessment and intervention by nurses to facilitate healthy outcomes. Identifying the effect of the suggested decision support tool on patient outcomes is one possible direction for a future work based on this study.

Application of the Transitions Theory to the Current Study

Figure 1 presents the adaptation of the transitions theory for the current study and provides examples of the variables that will be included under each of the theory components.

Figure 1: Adaptation of transitions theory to the current study

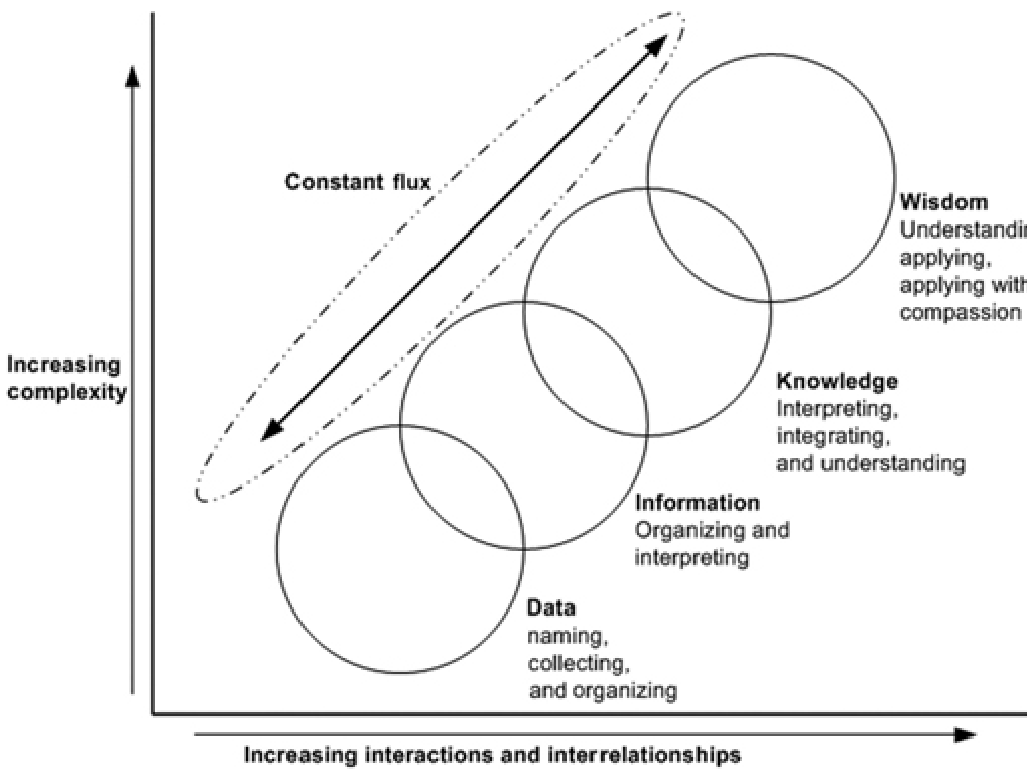


Data-Information-Knowledge-Wisdom framework

The Data-Information-Knowledge-Wisdom (DIKW) framework guided the conceptualization of how the present study fits into a broader domain of nursing informatics. Nursing informatics is often defined as a combination of computer science, information science and nursing science designed to assist in the management and processing of nursing data, information and knowledge to support the science and practice of nursing and the delivery of nursing care (Graves & Corcoran, 1989; Matney et al., 2011).

The development of the DIKW framework was urged by a search for a new theoretical model explaining the emerging field of nursing informatics in 1980-90s. In their seminal article, Graves and Corcoran (1989) outlined that data, information, and knowledge are foundational concepts for the specialty. Their framework was widely accepted by an international Nursing Informatics community (Matney et al., 2011; McGonigle & Mastrian, 2011). In 2008, the American Nurses Association revised the Scope and Standards for Nursing Informatics to include an additional concept, wisdom (American Nurses Association, 2008). The main components of the framework include (see Figure 2 adopted from American Nurses Association (2008)):

Figure 2: Data Information Knowledge Wisdom framework (adopted from: American Nurses Association, 2008)



- **Data**: are the smallest components of the DIKW framework. They are commonly presented as discrete facts; product of observation with little interpretation. In this study, data were all the discrete factors affecting patient severity, such as medical diagnosis (e.g. International Statistical Classification of Diseases (ICD-9) diagnosis #428.0: Congestive heart failure, unspecified) or living status (e.g.

living alone; living with family; living in a retirement community; etc.). A single piece of data, datum, often has little meaning in isolation.

- **Information**: might be thought of as “data + meaning”. Information is often constructed by combining different data points into a meaningful picture, given certain context. Information is a continuum of progressively developing and clustered data; it answers questions such as “who”, “what”, “where”, and “when”. For example, a combination of ICD-9 diagnosis #428.0 “Congestive heart failure, unspecified” and living status “living alone” has certain meaning in a context of older adult. Information is organized in unique way structured by a discipline, in this case, Nursing.
- **Knowledge**: is information that has been synthesized so that relations and interactions are defined and formalized; it is built of meaningful information constructed of discrete data points. Knowledge is often affected by a scientific discipline assumptions and central theories and is derived by discovering patterns of relationships between different clusters of information. Knowledge answers questions of “why” or ”how”.

  Central types of knowledge are tacit and explicit (McGonigle & Mastrian, 2011). Tacit is a personal, background and intuition driven knowledge that is hard to specify and formalize. In contrast, explicit knowledge is easy to formalize and capture by information systems. For instance, decision support computerized systems are using the explicit knowledge formalized by experts to suggest possible actions for practicing clinicians at the point of care.

  In this study, combining information such as the ICD-9 diagnosis #428.0 “Congestive heart failure, unspecified” and living status “living alone” with an additional information that an older man (78 years old) was just discharged from the hospital to home health with a complicated new medical regimen (e.g. blood thinners) could have indicated that this person is at a high risk for re-hospitalization due to drug-related adverse effects (e.g. bleeding).

- **Wisdom**: is an appropriate use of knowledge to manage and solve human problems (American Nurses Association, 2008; Matney et al., 2011). Wisdom implies a form of ethics, or knowing why certain things or procedures should or should not be implemented in healthcare practice. In nursing practice, wisdom guides the nurse in recognizing the situation at hand based on patients' values, nurse's experience, and healthcare knowledge. Combining all these components, the nurse decides on a nursing intervention or action. Benner (2000) presents wisdom as a clinical judgment integrating intuition, emotions and the senses. Using the previous examples, wisdom could be displayed when the home health manager or intake nurse consider prioritizing the elderly HF patient with blood thinners for an immediate, patient tailored intervention, such as a first nursing visit within the first 24 hours of his arrival to home (or even before) or a call to patient's primary care provider (to make sure that the dosage of the blood thinners is appropriate).

As shown in Figure 2, the boundaries of the DIKW framework components are not strict; rather, they are interrelated and there is a "constant flux" between the framework parts. Simply put, data are used to generate information and knowledge while the derived new knowledge coupled with wisdom, might trigger assessment of new data elements (Matney et al., 2011). Finally, the DIKW framework serves as a conceptual model guiding the linkage between the theory and practice (Matney et al., 2011), while discipline specific theories (such as the transitions theory) are needed to explore the required data elements and to formalize discipline specific knowledge.

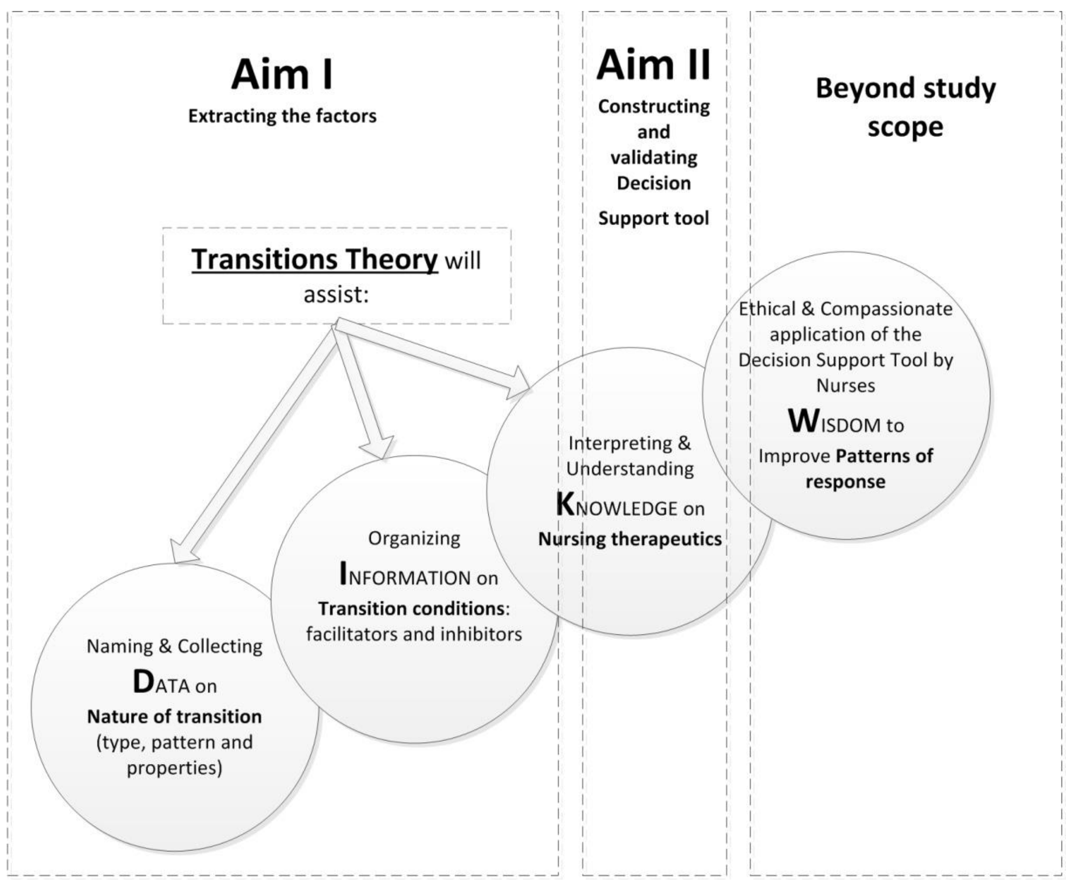
Merging the Frameworks: Applications for this Study

I used the discipline specific transitions theory (Meleis, 2010) to examine the phenomenon of interest, namely the process of an individual's transition from hospital to home health settings. The transitions theory guided the analysis of factors (disease characteristics, medications, patient needs, social support characteristics) addressed by Aim 1 of this study. The DIKW framework (American Nurses Association, 2008) was used to explicitly present all the Informatics steps during the construction of a decision support tool, the final goal of this study addressed in Aim 2.

In summary, the transitions theory guided the selection of discrete Data points during the transition process (patient's clinical, environmental and social support characteristics); creation of meaningful Information about the patient's medical and social conditions (case studies); and analysis of the linkages between different information clusters to create a hierarchy of factors representing the Knowledge of patient's priority for the first home health nursing visit. This knowledge was used to create a tool to support effective patient prioritization at admission to home health. Thus, the proposed study addressed the DIK components of the DIKW framework. The wisdom component is outside of the scope of the current study and should be addressed by clinicians in the field, according to tacit and otherwise non- generalizable knowledge present in every clinical situation (e.g. ethics, practice regulations in each particular state in the US, organizational structure of the home health agency, etc.). The goal of the proposed patient prioritization decision support tool is to advance nursing knowledge and promote home health nurses' wisdom at the point of patient admission to home health agency. Figure 3 presents the combination of the frameworks to address study aims.

Other researchers in nursing informatics might consider this merging approach to generate useful theoretical frameworks for their studies. My recent manuscript titled "The Hitchhiker's Guide to nursing informatics theory: using the Data-Knowledge-Information-Wisdom framework to guide informatics research" provides a detailed description of the suggested approach (Topaz, 2013).

Figure 3: Merging theoretical frameworks



REVIEW OF LITERATURE

Home Health in the US

The overall goal of the present home health care system is to provide treatments for an illness or injury and to help patients regain independence and control over their health condition. For chronic conditions, home health aims to assist patients with maintaining the highest level of independent function and teach patients the required self-care skills to live with their disease (Murkofsky & Alston, 2009). When possible, providing healthcare at home is safe and less expensive than acute care or long term services (The Joint Commission, 2011). With the current advances in medical technology and pharmaceutics, many patients and healthcare stakeholders prefer care at homes over emergency room visits, hospitalizations or nursing homes (American Medical Association and American Academy of Home Care Physicians., 2007; Murkofsky & Alston, 2009).

Currently, Medicare is the single largest payer for home health. To be eligible for Medicare home health services, patients must meet the following criteria (Centers for Medicare & Medicaid Services, 2012a): (1) home care must be medically necessary and supervised by the patient's physician; (2) care must require a registered nurse (RN), physical therapist, or speech-language pathologist; (3) nursing care must be part time or intermittent; and (4) the patient must be homebound, meaning that leaving home is a considerable and taxing effort. Patients might be absent from their homes but that should be infrequent and patient should rely on the assistance of another person or assisting device. Other absences from the home are permitted (e.g. occasional trips to the barber, a walk around the block, or a drive; attendance at a family reunion, funeral, graduation, or other unique event) as long as they are infrequent and require considerable effort (Centers for Medicare & Medicaid Services, 2012a).

Current Trends in Home Health

Rapid population ageing, increases in the number and severity of chronic diseases, and growing complexity of the medication regimens require healthcare researchers and stakeholders to reconsider the existing models of care (Centers for Medicare & Medicaid Services, 2012b). It is evident that more healthcare services will be needed, especially those provided outside of the hospitals. In home health, the quantity of services was the main driver for reimbursement from 1965 to 2000 (see Appendix I for more details on the historical development of the US home health). Transition to a Prospective Payment System, introduction of a quality of care and outcome measures facilitated the implementation of quality of care driven approach (Murkofsky & Alston, 2009).

Several recent legislative and regulation trends represent the transition to a more collaborative, quality oriented care model assisted by health information technology. First, the Affordable Care Act, or the healthcare reform, encourages more home and community services in several cost-effective ways (Manchikanti, Caraway, Parr, Fellows, & Hirsch, 2011; U.S Senate, 2011). The Act makes it easier for the states to add home health services to their Medicaid programs. In the past, states needed to renew their federal approval every three to five years. The law also makes home health available to more individuals. For example, it is suggested to expand Medicaid home health coverage for beneficiaries that have either: at least two chronic conditions (e.g. diabetes, asthma, obesity, heart disease, mental condition, and substance abuse disorder); one chronic condition and being at risk for another; or one serious and persistent mental health condition (Kaiser Family Foundation, 2011). The Affordable Care Act has also enacted several rehospitalization reduction programs. For instance, starting in October 2012, hospitals across the US are financially penalized if their patients with acute myocardial infarction, heart failure or pneumonia are rehospitalized with 30 days from hospital discharge (Center for Medicare and Medicaid Services, 2012b). Currently, the scope of financial penalties (adjustment in payments for treating these patients) is increasing and new conditions are being considered.

The general aim of this dissertation was to address these important legislative and regulatory trends and contribute to the fast developing care coordination efforts by constructing a decision support tool that will enable better linkage and thereby facilitate the transition between inpatient and home health settings. The proposed clinical prioritization tool is also intended to help clinicians to provide individualized patient care and enable better decisions on health resource distribution at the point of care.

The Problem: Inappropriate Patient Prioritization at Admission to Home Health

Current home health services suffer from several central issues, such as insufficient staffing (McAuley, Spector, & Van Nostrand, 2008), home health nurses' and managers' job dissatisfaction (Samia, Ellenbecker, Friedman, & Dick, 2012; Sochalski, 2004), disparity in resource allocation and numbers of agencies between rural and urban areas (Franco, 2004; Hartman, Jarosek, Virnig, & Durham, 2007; McAuley, Spector, Van Nostrand, & Shaffer, 2004), low workforce retention levels (Cushman, Ellenbecker, Wilson, McNally, & Williams, 2001; Ellenbecker, Porell, Samia, Byleckie, & Milburn, 2008; Smith-Stoner, 2004), low levels of nurses' clinical knowledge (Albert, 2006; Delaney, Apostolidis, Lachapelle, & Fortinsky, 2011), and fraud and abuse (MedPac, 2014). In this proposal, I focus on an additional critical issue that is currently unaddressed by home health researchers but has a high potential to improve the provided services, namely the process of patient admission to home health services.

Population of Interest: Patients Admitted to Home Health Agencies (HHA) from Hospital

Currently, about 35% of the home health patients (or approximately 4.2 million patients) are admitted to HHA from hospitals (MedPac, 2014). These patients are a distinct population with unique needs and problems. It was recently suggested that patients discharged from hospitals often have a Post-Hospital Syndrome- an acquired, transient condition that puts them at a great risk for poor outcomes (Krumholz, 2013). During a hospitalization, many patients are sleep deprived (Friese, 2008; Young et al., 2008), experience high levels of stress and inadequate nutrition (Dupertuis et al., 2003; Singh et al., 2006). At the time of discharge, patients cannot deal effectively with health threats, and suffer from impairments in physiological systems and depleted reserves (Krumholz, 2013).

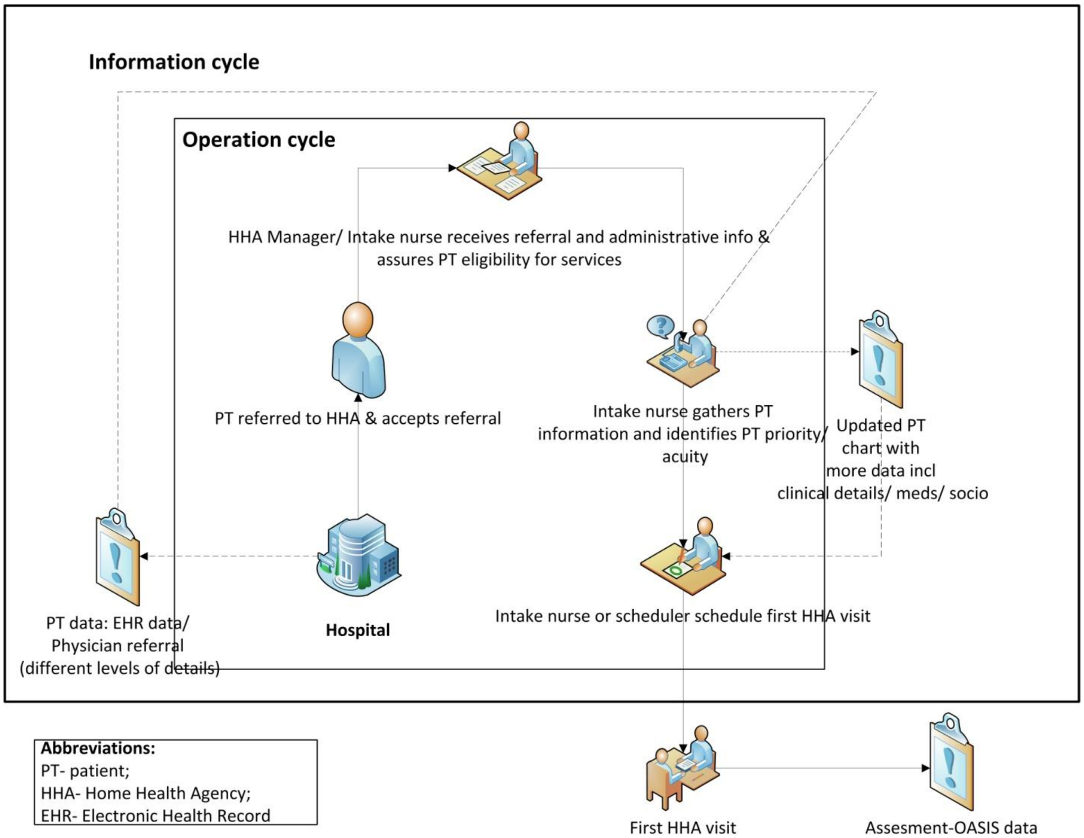
A growing body of evidence (O'Connor, 2012; Rosati, Huang, Navaie-Waliser, & Feldman, 2003) suggests that patients admitted from hospitals often have the most complex clinical problems and needs that lead to higher risk of rehospitalization or other poor outcomes. For example, patients discharged from hospitals often require complex wound care or intravenous antibiotic therapy while patients referred to HHA from community, might have an exacerbation of a known chronic condition (such as HF or diabetes mellitus) (Goldberg, 2011).

Among patients admitted from hospitals, the number of rehospitalizations is generally higher than for patients admitted from other settings; some evidence suggests that up to 34% of patients discharged from hospitals are rehospitalized within 30 days and these numbers are growing significantly beyond this time frame (Anderson et al., 2005; Berry et al., 2011; Markley, Sabharwal, Wang, Bigbee, & Whitmire, 2012). Because of these differences, identifying factors that can be used to help prioritize patients for the first HHA visit should be identified within each particular population (admission from hospital vs. other admissions). The need in providing better care for those patients was also explicitly indicated in the recent report to Congress conducted by the Medicare Payment Advisory Commission (MedPac, 2014). This population of patients discharged from hospitals to home health is the focus of this dissertation study.

The Typical Home Health Admission Process

Figure 4, developed as a result of our pilot interviews with home health managers and intake nurses (Topaz et al., 2013) and clinical experts on the study team, depicts the typical home health admission process. In agreement with the DIKW conceptual framework describing the flow of information to generate knowledge, two cycles of the home health admission process can be identified; 1) Operation cycle and 2) Information cycle. Operation cycle includes different steps of the admission process, starting from hospital discharge to the first nursing visit. Information cycle is concerned with what information is being transferred to whom during the hospital to home transition. Both cycles require varying levels of involvement of patients and their family members and healthcare providers (referring source, home health managers, intake nurses, schedulers, field nurses conducting the first visit).

Figure 4: Typical home health admission process



In general, the typical home health admission process starts with recognition that home health services are needed. A primary care physician, hospitalist, hospital discharge coordinator, a nurse or a family member can identify this need. Then, a physician signed referral for home health services is acquired. Ideally, the patient is then given a number of options for a possible home health provider. When a particular agency is selected, its representative -usually the intake nurse or home health agency manager- receives the referral, identifies patient’s eligibility and the insurance that will reimburse for the care. If the patient is eligible for services, more information is gathered about the patient (using various sources such as electronic health record, phone call to the patient or referral source, etc.) and an initial nursing assessment visit is scheduled.

The first home health visit (usually by a Registered Nurse) is one of the most important steps of the home health episode; during this visit, the initial patient assessment is conducted and the care plan is created according to the patient's unique needs and problems. At this visit, the OASIS assessment is performed (CMS required comprehensive data set used for payment and quality of care evaluation). Currently, CMS requires that initial assessment visit must be held either within 48 hours of referral, or within 48 hours of the patient's return home, or on the physician-ordered start of care date (Centers for Medicare & Medicaid Services, 2012a). Other insurers might have various requirements for the first nursing visit, but generally, some time frame is usually present (Topaz et al., 2013). Unfortunately, no conclusive statements on the timing of the first nursing visit for non-CMS patients might be suggested as these requirements vary from state to state and from one home health agency to another.

Identifying patients' priority for the first nursing assessment visit is critical, especially for individuals with pressing healthcare needs. Nationwide, up to 60% of unplanned hospitalizations from home health (hospitalization rate from home health stands at about 30%) are happening within the first two weeks of services (O'Connor, Hanlon, & Bowles, 2014; Rosati & Huang, 2007). Unfortunately, the 48 hours CMS's time period for the first visit cannot be applied for the entire patient population. The times for the first nursing visit should be tailored individually based on a set of patient and caregiver characteristics, such as patient's diseases or the amount and type of social support available for the patient after hospital discharge. In the next paragraphs, I present several factors affecting the admission process and number of outcomes that can be possibly worsened by inappropriate by patient prioritization.

Factors Affecting the Admission Processes

Several clinical, organizational and financial factors affect the process of admission to a HHA. Since no studies focus specifically on factors affecting HHA admission, we conducted a qualitative study exploring the current admission processes. While still working on in-depth data analysis, next paragraphs present some preliminary findings that emerged so far (Topaz et al., 2013). Overall, 12 semi-structured interviews were conducted with a purposive sample of 12 HHA managers and experienced intake nurses from nine agencies of different sizes and in different geographic areas (West, East, Midwest and South) of the US. Interviews focused on sets of factors (i.e. patient characteristics, policies and procedures) that influence decisions to prioritize initial nursing visits. Interview transcripts were coded using software for qualitative analysis to reveal central themes.

We found that many HHA received insufficient patient information from the referral sources (e.g. blurred fax documents, disconnected telephone numbers etc.) while others had access to excessive and complex patient information (e.g. from hospital electronic medical records). Neither situation was informative for the intake nurse needing to understand patients' severity. On one hand, insufficient information was clearly not enough while on the other hand, looking at the full patient record at the time of current or previous hospitalizations didn't necessarily provide information critical for outpatient settings (e.g. living status, availability of social support). Figure 5 provides an example of a HHA referral form; it collects very little administrative (name/phone number/insurance type) and clinical information (primary diagnosis/reason for HHA referral) on the patient. While several promising projects to construct a continuity of care document that includes all the critical patient information are ongoing (National Quality Forum, 2012), no clinical standard for home health exists.

Overall, our participants highlighted the importance of detecting the unstable patients with greater risk for negative health outcomes and prioritizing them for care (Topaz et al., 2013). However, inconsistent strategies were used to identify those patients. Some nurses reported prioritizing patients based on clinical factors, such as presence of HF or COPD while others prioritized based on social factors (caregiver availability) or previous care settings. Yet others, made patient prioritization decisions based on their personal experience and intuition. Only one agency used an internally developed tool for patient prioritization but it was not thoroughly tested or validated. Those results underscore the need for consistent, evidence based approaches for patient prioritization upon admission to home health.

Figure 5: Example of a current home health referral

PATIENT REFERRAL FORM

NAME: ______________________ S.S.#: __ __ __ / __ __ / __ __ __

ADDRESS: ______________________ D.O.B.: __ __ / __ __ / __ __ __ __

______________________ PHONE: (__ __ __) __ __ __ - __ __ __ __

INSURANCE

Plan #1: ______________________ Policy No.: ______________ (e.g., Medicare)

Plan #2: ______________________ Policy No.: ______________ (e.g., AARP)

EMERGENCY CONTACT

Name: ______________ Phone: ______________

Address: ______________________

PRIMARY DIAGNOSIS: ______________________

MEDICALLY NECESSARY HOME CARE SERVICES:

☐ **Skilled Nursing** ☐ **Physical Therapy** ☐ **Home Health Aides**

☐ **Occupational Therapy** ☐ **Speech Therapy** ☐ **Medical Social Work**

IF PATIENT'S PRIMARY INSURANCE IS TRADITIONAL MEDICARE,
PLEASE COMPLETE THIS SECTION

DATE OF LAST FACE TO FACE ENCOUNTER: __ __ / __ __ / __ __ __ __

Traditional Medicare patients are required to have a face to face encounter with a MD, APRN or PA within 90 days prior to, or 30 days following, the start of home care.

CLINICAL FINDINGS TO SUPPORT NEED FOR HOME CARE: ______________________

REASON PATIENT IS HOMEBOUND: ______________________

PHYSICIAN SIGNATURE: ______________________ **DATE** __ __ / __ __ / __ __ __ __
MD MUST SIGN HERE

PHYSICIAN NAME PRINTED: ______________________

PLEASE CALL TO CONFIRM OUR RECIEPT OF THIS FAX

☐ **CHECK BOX IF NEXT DAY VISIT NEEDED**

Outcomes Affected by Flaws with the Current Prioritization Methods

Inappropriate patient prioritizing (or inadequate nursing therapeutics as defined by Meleis's transitions theory) at the time of admission to home health services might have several short and long term effects. For instance, it might increase the risk of unplanned hospital admissions. Nationwide evidence shows that about 60% of unplanned hospitalizations from home health (hospitalization rate from home health stands at about 30%) are happening within the first two weeks of services (O'Connor, Hanlon, & Bowles, 2014; Rosati & Huang, 2007). Our unpublished data from a large academic healthcare institution in Philadelphia presents similar trends; about 26% of the patients were rehospitalized within 60 days of the start of home health services after an index hospitalization. Half of these patients were rehospitalized within the first two weeks (Bowles, 2012).

Inappropriate patient prioritization is one of the factors significantly affecting the rates of rehospitalizations, especially those close to hospital discharge. First, it is well documented that many patients discharged from hospitals are not ready for discharge and have problems complying with the complex medical regimens and new self-care activities (defined as Properties of the transitions experience in transitions theory) (Barnason et al., 2012; Bobay et al., 2010; Coffey & McCarthy, 2012; Foust et al., 2012; Weiss et al., 2007). An average home health patient suffers from at least four medical conditions, including hypertension (41%), heart disease (31%), diabetes mellitus (30%), and COPD (13.5%) (Caffrey et al., 2011). Recent data suggests that a typical home health patient takes 8 medications on average and about 40% of the patients need to remember special instructions (e.g. take on alternative days, dissolve) (McDonald et al., 2012). Critically, many of these patients are not seen by a physician in their community setting; nationwide data show that over half of patients who were rehospitalized within 30 days did not visit a physician's office between the two admissions (Jencks et al., 2009). Many other studies confirmed this alarming picture and showed that 30% to 60% of the patients are not seeing their primary care providers for the follow up visits for a variety of reasons such as patient non-adherence and providers lack of attention to this patient population (Alper et al., 2013; Grafft et al., 2010; Hernandez et al., 2010; Misky et al., 2010; C. Murtaugh, 2013; Sharma et al., 2010).

The combination of poor discharge readiness, high clinical complexity and poor follow-up by primary care providers (defined as Transition inhibitors by transitions theory), makes home health patients vulnerable to poor care outcomes (e.g. rehospitalizations or death). For instance, nationwide data shows that more than 13% of home health patients experience adverse events (e.g. medication mistakes) (Madigan, 2007). On the long run, inappropriate patient prioritization at the admission to HHA might possibly contribute to the increased caregiver and patient burden (Foust et al., 2012) or higher chances of admission to a nursing home (Gaugler, Duval, Anderson, & Kane, 2007).

Factors Associated with Poor Outcomes among Home Health Patients

In general, factors associated with poor outcomes for home health patients (or transition conditions according to transitions theory) might be categorized under three domains: 1. Sociodemographic characteristics 2. Clinical history and 3. Functional status.

Sociodemographic characteristics significantly contribute to patients' ability to cope with their medical conditions, thus affecting short and long term rehospitalizations and other care outcomes (Fortinsky et al., 2006; O'Connor, 2012; Rosati et al., 2003). It is well established that patients who lack informal caregivers and live alone or receive little or no help from their informal caregivers are at a higher risk for adverse outcomes, e.g. rehospitalizations (O'Connor, 2012; Rosati et al., 2003). Other factors include being a white woman or Hispanic racial background; having a previous history of home health services or hospitalization within 30 days; and being dually eligible (Medicare/Medicaid) (O'Connor, 2012; Rosati et al., 2003; Rosati & Huang, 2007).

Several clinical history factors are associated with home health patients' poor outcomes. First, having one or several of the following factors was found to contribute to patients admission to hospitals: common chronic condition such as HF, COPD, diabetes mellitus with a wound or renal failure, chronic skin ulcers, and depression (Allaudeen, Vidyarthi, Maselli, & Auerbach, 2011; Mudge et al., 2011; O'Connor, 2012; Rosati et al., 2003; Rosati & Huang, 2007; Strunin, Stone, & Jack, 2007); more than four secondary diagnoses or a complex medication regime (e.g. more than five medications) (Rosati et al., 2003; Rosati & Huang, 2007). Use of high risk medications (e.g. antibiotics, glucocorticoids, narcotics, antiepileptic medications, antipsychotics, antidepressants) was often associated with poor outcomes (Allaudeen et al., 2011; Budnitz et al., 2006; Budnitz, Shehab, Kegler, & Richards, 2007; Budnitz, Lovegrove, Shehab, & Richards, 2011).

Functional status risk factors include requiring assistance with ADLs, IADLs and taking medications (Fortinsky et al., 2006; O'Connor, 2012; Rosati et al., 2003; Rosati & Huang, 2007). In some cases, OASIS functional score was used to identify patient priority for services (Bowles & Cater, 2003; O'Connor, Hanlon, & Bowles, 2014). In this study I aim to estimate the priority for the first nursing visit before the OASIS assessment (the OASIS conducted during the first nursing visit).

Screening Tools and Clinical Decision Support Systems

Screening Tools

A few screening tools have been developed for the home health setting, however there are several major limitations that prevent their use to identify the priority for the first nursing visit:

- Most of the existing tools were constructed based on the OAISIS dataset (the OASIS assessment performed during the first nursing visit);
- Few of the existing tools were rigorously constructed or validated (the tools are mostly internally developed by different HHAs).
- Some tools were developed internationally and have limited applicability to the US home health settings.

For example, the Quality Improvement Organization at the West Virginia Medical Institute (supporting the Home Health Quality Campaign under contract with the CMS), have developed a “Hospitalization risk assessment” tool. The tool is based on predictors of hospitalizations identified in two home health studies examining the OAISIS data (Fortinsky et al., 2006; Rosati et al., 2003). However, the “Hospitalization risk assessment” tool does not provide any guidance on which patients need to be prioritized, but rather it is an eclectic list of factors associated with hospitalizations from home health settings (Figure 6). As suggested in the tool’s instructions, each HHA is supposed to “select a threshold score to target patients at high risk” based on whether the patients have certain characteristics or not (for example HF or lives alone). The tool also notes that the constructed risk is “… for convenience only and has not been tested or validated.”

Another example of an internationally developed screening approach is the Canadian guideline to determine the priority of home health patient’s visit (Figure 7). This guideline developed by one of a large state Health Authorities in Canada suggested that home health agencies should stratify its incoming patients into six priority levels based on their risk for poor outcomes (from intolerable risk to tolerable risk). Each priority level is associated with a specific time frame. For instance, patients ranked as priority one are divided into two sub-categories: those that should receive a visit/intervention within 12 hours (same day visit) and those requiring visit/intervention within 12-24 hours. The Health Authority provides several general examples of patients in this category, such as a “Sudden change in patient condition” or “Acute respiratory condition”. The priority levels are then estimated by the intake nurses of each agency (I learned about the tool and the process of patient prioritization through a personal correspondence with the department). Unfortunately, this tool was not validated and has very limited applicability in the US because of the difference in the time frames for the first nursing visit: 48 hours in the US versus up to 4 weeks in Canada. In our pilot study of home health admission, we found one HHA internally developed tool for patient prioritization, however, this tools was not publically reported or validated Topaz et al., 2013).

Figure 6: Hospitalization risk assessment tool

Hospitalization Risk Assessment

Purpose: Screening tool to identify those at risk for hospitalization.

Patient Name: ____ Record # _________________

Date: ______________________

Prior pattern: Check all that apply	
❑ > 1 Hospitalizations or ER visits in the past 12 months (M1032)	❑ History of falls * (M1032 and M1910)
Chronic conditions: Check all that apply (M1020/1022/1024)	
❑ HF (M1500 and M1510)	❑ Chronic skin ulcers *(Wound consult if indicated for any wounds)*
❑ Diabetes	
❑ COPD	❑ HIV/AIDS
Risk Factors: Check all that apply	
❑ Discharged from hospital or skilled nursing facility (M1000)	❑ Help with managing medications needed (M2020) ► ★
❑ More than 2 secondary diagnoses (M1022 and 1024)	❑ Non-compliance with medication regimen ♦ ★
❑ Low socioeconomic status or financial concerns ♦	❑ Confusion (M1710) ♦ ★
❑ Lives alone (M1100) ► ♦	❑ Pressure ulcer (M1300, M1302 and M1306) ★
❑ Inadequate support network (M1100) ♦	❑ Stasis ulcer (M1330) ★
❑ ADL assistance needed ► (M2100 and M2110)	❑ Overall Poor Status/Prognosis (M1034) ■
❑ Home safety risks ► ♦	❑ Low literacy level ♦
❑ Dyspnea (M1400 ► ★	❑ Depression (M1730) ♦
► Consider Therapy referral (PT, OT, ST) ♦ Consider MSW referral	■ Consider Hospice referral ★Consider RN referral, if not ordered

Total # of checked boxes is ___. **Your agency may want to select a threshold score to target patients at high risk.** *(For example: 5 or greater risk factors may indicate that the patient is at risk for hospitalization.* Note: This number is for convenience only and has not been tested or validated. The agency may modify the score based upon the needs of their patient population.)

Carry out patient specific interventions as appropriate/ordered, if patient is at risk for hospitalization: (Coordinate with M2250)

Referrals: ❑ SN ❑ PT ❑ OT ❑ ST ❑ MSW ❑ HHA ❑ Dietary Consultant ❑ Other:	❑ Medication Management ❑ Medication Reconciliation • Assess patient's: knowledge, ability, resources and adherence • Education	❑ Patient/family education ❑ Enrollment into a disease management program (specify):
❑ Hospice/Palliative Referral	❑ Phone Monitoring	Immunizations (M1040, M1045, M1050, M1055) ❑ Influenza ❑ Pneumococcal
❑ Individualized Patient Emergency Care Plan	❑ Front-loading Visits	❑ Care Coordination (Physicians, hospitals, nursing homes…)
❑ Fall Prevention Program	❑ Telemonitoring	❑ Other:

Notify the following, as appropriate, if patient is at risk for hospitalization:

❑ Physician Correlate with M2250 for physician notification of specific parameters/interventions	❑ Interdisciplinary Team ___________ ❑ Patient/family/caregiver	❑ On Call Staff ❑ Agency Case Manager	❑ Payer: (e.g. Managed Care Organizations) ❑ Other:

Clinician Signature: ____ Date:___________

Adapted from Personal Touch Home Care, VA 6/25/04 Professional Practice Model.
Revised 12/21/09 to correlate with OASIS-C.

The following articles provide more information on risk assessments:

Rosati, R.J., Liping, H., Navaie-Waliser, M., & Feldman, P.H. (2003) Risk Factors for Repeated Hospitalizations among Home Healthcare Recipients. *Journal for Healthcare Quality*, 25(2).
Fortinsky, RH, Madigan, EZ, Sheehan, TJ, Tullai-McGuinness, S. & Fenster, JR. (2006) Risk factors for hospitalization among Medicare home care patients. *West J Nurse Res*, 28(8).

This material was prepared by the West Virginia Medical Institute, the Quality Improvement Organization supporting the Home Health Quality Campaign, under contract with the Centers for Medicare & Medicaid Services (CMS), an agency of the U.S. Department of Health and Human Services. Publication number: 9SOW-WV-HH-BBK-012710A App. 01/10.

Figure 7: Health Authority guidelines for determining priority of visit

VANCOUVER ISLAND health authority

Vancouver Island Health Authority Guidelines for determining Priority of Visit
Adapted from VCH Guidelines – August 2008

Goal: Access to services across VIHA will be maintained based on client need. (Once eligibility has been established, priority for program admission is based on consideration of client's needs as assessed by central intake/community access coordinators/health care professional to assist in the management of health care demands).

Inclusion: This goal relates to all Home & Community Care Services, including but not limited to: home care nursing, occupational and physical therapy, case management, nutrition, social work.

Guidelines:

1. All referrals to community services, and all existing community clients, will be prioritized based on the following criteria.
2. Where conditions exist that may result in an inability to schedule clients according to the following criteria, the community service/program, for example, due to low staffing or high referrals, the program/service will follow a consistent protocol. In decision-making, consider:
   - Safe environment for staff and client;
   - Clinical Practice Guidelines or routine practice;
   - Regional Policy regarding Admission/Discharge criteria;
   - Affect on other programs/networks

Priority 1, Intolerable Risk Visit/Intervention Within 24 hours **Priority 1A** – Visit/Intervention within 12 hours (same day service) **Priority 1B** – Visit/Intervention within 12-24 hours	Professional assessment that there is high probability of immediate negative outcome if not seen within 24 hours
Priority 2, Tolerable Risk Visit/Intervention Required Within 48 hours	Professional assessment that there is a high probability of negative outcome to health, safety of client/family and/or the development of primary and/or secondary complications if situation persists over 48 hours.
Priority 3, Tolerable Risk Visit/Intervention Within 1 week	Professional assessment that there is a high probability of negative outcome or secondary complications will occur if situation persists over 1 week.
Priority 4, Tolerable Risk Visit/Intervention Required Within 2 weeks	Professional assessment that moderate probability of negative outcome or secondary complication will occur if situation persists up to 2 weeks:
Priority 5, Tolerable Risk Visit/Intervention Can Occur Between 2 to 4 Weeks	Professional assessment that there is minimal probability of a negative outcome or pre-scheduled visits/interventions that can occur within a variable timeframe.
Priority 6, Pending Referral (no date specified)	Pending Referral (date not yet specified) • Client's referral to the service is delayed.

Decision Support Systems

Clinical Decision Support Systems (CDSS) include a variety of systems and tools designed to impact clinician decision making about individual patients at the point in time that these decisions are made (Berner, 2007). CDSSs are becoming ubiquitous in modern healthcare; in the US, these trends are facilitated by the recent Meaningful Use regulation requiring most of the healthcare providers to use these tools by 2020 (Office of the National Coordinator, 2012). In general, CDSS might be categorized into two categories: 1. Knowledge- based systems that use pre-defined experts knowledge to create patient specific suggestions and 2. Nonknowledge-based systems that employ machine learning and other statistical pattern recognition approaches to come up with an appropriate recommendation (Berner, 2007; Greenes, 2007). This study aims to construct a knowledge- based decision support system since no large and high quality secondary data pool exists, which is often a necessary preliminary requirement for non-knowledge-based system construction (Berner, 2007).

In modern healthcare, CDSSs are widely applied throughout settings and clinical disciplines. CDSSs are used to provide alerts and reminders (Ash et al., 2012; Sahota et al., 2011; Shojania et al., 2009; Smithburger, Buckley, Bejian, Burenheide, & Kane-Gill, 2011); allow incorporation of clinical guidelines into clinical processes (Damiani et al., 2010; Latoszek-Berendsen, Tange, van den Herik, & Hasman, 2010; Sahota et al., 2011; Tomaszewski, 2012); construct order sets (Ash et al., 2012; Cufar, Droljc, & Orel, 2012; Forseen & Corey, 2012; McGreevey, 2013; Stabile & Cooper, 2012); support diagnostics (Roshanov et al., 2011; Sahota et al., 2011; Tomaszewski, 2012); and allow easy access to medical reference information (Garg et al., 2005; Jao, 2011). CDSSs are also used to assist with care provided throughout the health continuum, from newborn care (Fiks, 2011; Kadmon et al., 2009; Longhurst, Turner, & Burgos, 2009; Stultz & Nahata, 2012) to chronic disease (Leslie & Denvir, 2007; Roshanov et al., 2011) and end of life issues (Elvidge, 2008; Murray, Miller, Fiset, O'Connor, & Jacobsen, 2004). CDSSs have proven potential to improve healthcare, especially process outcomes such as adherence to care protocols or prescription of recommended treatments (Roshanov et al., 2011).

In nursing, the development and application of CDSSs is a relatively new field (Anderson & Willson, 2008). Recently, several nursing CDSSs were developed and applied to treat and prevent pressure ulcers (Alvey, Hennen, & Heard, 2012; Beeckman et al., 2012; Fossum, Alexander, Ehnfors, & Ehrenberg, 2011; Kim & Park, 2012); glicemic control (Mann, Jones, Wolf, & Wade, 2011); and fall prevention (Dykes et al., 2010). Our team was also involved with a development of clinical decision support tool for HF patients in home health settings (Radhakrishnan, Topaz, & Masterson-Creber, 2013; Topaz, Shalom, Masterson-Creber, Rhadakrishnan, & Bowles, 2013). There is only scarce evidence on CDSSs in care coordination and transitions; the most significant work in this field is conducted by Dr. K. H. Bowles (Bowles et al., 2009; Bowles, Holland, & Potashnik, 2012) and Dr. D. Holland (Holland & Hemann, 2011; Holland, Knafl, & Bowles, 2012; Holland & Bowles, 2012). These nurse-researchers were also one of the first to show that CDSSs impact patient outcomes related to timely and personalized discharge planning. For instance, Holland & Bowles (2012) showed that after application of a decision support tool that assisted clinicians to conduct standardized patient discharge assessment, patients reported fewer unmet needs and fewer problems complying with the discharge instructions. Similarly, Holland and Hemann (2011) showed that application of a discharge planning decision support tool resulted in a clinically meaningful decrease in length of stay for a group of older patients at greater risk for complex discharge plans. Additional decision support tool developed by Holland, the Early Screen for Discharge Planning (ESDP), was also found effective in identifying patients for early discharge planning interventions (Holland et al., 2012). Bowles and colleagues (Bowles et al., 2013) have shown that application of a discharge decision support tool (D2S2) assisting nurses with identifying patients that require post-acute care, decreases 30 and 60 days rehospitalizations to hospitals. The proposed study will continue this line of work and be the first to develop a decision support tool to enhance care transitions to home health settings.

Thus far, only one Canadian study has developed a decision support tool somewhat similar to the one developed in this study (Hirdes, Poss, & Curtin-Telegdi, 2008). The Canadian team aimed to develop a decision support tool to assist home health professionals with allocating the scarce resources appropriately. The researchers analyzed international secondary data based on the Resident Assessment Instrument - Home Care (RAI-HC) to identify predictors for nursing home placement, caregiver distress and for being rated as requiring alternative placement. The constructed Method for Assigning Priority Levels (MAPLe) algorithm was a strong predictor of all three outcomes in a Canadian derivation sample (it was also validated with international datasets with mixed success). Unfortunately, no further reports on the use of the tool in practice were identified. This project was different from the proposed study in several central ways. First, to construct and validate the tool, the researchers used secondary data from different countries including Canada, the U.S., Japan, Iceland, Italy etc. It is reasonable to expect that the quality of documentation, healthcare systems, patient characteristics and other factors are different between the international settings; the researchers indeed identified that their tool had a significantly different predictive ability in each of the countries. Second, the constructed tool used the comprehensive assessment data gathered at the first home health visit. Thus, the MAPLe algorithm (Hirdes et al., 2008) would not allow intake nurses and HHA managers to prioritize patients appropriately for the first visit.

These significant limitations of the existing data sources led to a decision to use comprehensive patient case summaries collected by Bowles' team for an ongoing study. To answer the study aims, I used a sub-set of patients that were offered a home health referral at their discharge from the hospital.

Summary: Gaps That Remain and the Present Project

In the US, home health services developed significantly throughout the last century. Today, HHAs offer a variety of healthcare services for millions of patients every year. Recent changes in legislative environment and financial incentives are aligned towards improving the coordination of care and personalized treatments through the use of sophisticated standardized tools supporting clinicians' decision making.

Home health services have high potential to improve patients' outcomes, especially when provided at the right time to the right individuals. This project examined one of the critical elements of the home health care episode, the process of admission to HHA. Because of the high rates of rehospitalizations and complexity of medical conditions, the focus was placed on the population of patients transitioning from hospitals to HHA. For these patients, the combination of several clinical, organizational and financial factors might result in inappropriate patient prioritizing at admission to

HHA, and there is lack of evidence to assist intake nurses and HHA managers to make these important decisions.

Recent evidence (Markley, Sabharwal, Wang, Bigbee, & Whitmire, 2012; McDonald et al., 2008; McDonald et al., 2012; O'Connor, Hanlon, & Bowles, 2014) shows that it is critical to identify patients at risk for poor outcomes (e.g. rehospitalizations due to adverse medication effects) and intervene within an appropriate time frame. Currently, the CMS requires that all the patients admitted to HHAs have to be seen by an agency representative within the 48 hours of admission. However, recent nationwide evidence shows that at least 11% (SD 10.7%) of the patients are not seen within this time frame (Center for Medicare and Medicaid Services, 2013a). Several clinical, sociodemographic and functional status characteristics were found to be associated with poor outcomes, however, no one study has previously focused on the process of HHA admission.

To address gaps in the literature, the proposed study created and validated a decision support tool to assist with identification of the patient’s priority for the first nursing visit. The priority is suggested by experts based on the patient characteristics. Comprehensive case summaries reflecting nationwide distribution of older adult patients referred to home health services- including factors related to patients’ medical and social status (for detailed description of data sources and factors included, see Methods section and Table 1)- were used to elicit experts’ knowledge. The proposed tool might be used to assist home health managers and intake nurses with prioritizing patients for a first nursing visit and healthcare services (such as telehealth).

Findings from this study have the potential to reduce the high variability of factors used to prioritize patients for the first nursing visit in the US. In addition to addressing gaps in knowledge, the proposed study meets several recommended research priorities including: enhancing care coordination and linkage (Grossman, 2011) and making timely and patient-centered care decisions (Agency for Healthcare Research and Quality, 2012).

CHAPTER3: DESIGN AND METHODS

The overall purpose of this study design was to create a decision support tool to assist home health personnel with making decisions about patient's priority for the first home health visit. A predictive design was used to identify the disease characteristics, medications, patient needs, social support characteristics and other factors associated with priority for the first visit at the admission to a HHA based on expert knowledge. This study used nurses with expertise in transitional care and care coordination who reviewed patient case summaries generated from electronic health records and determined the priority for the first nursing visit. Patient summary characteristics associated with expert's decisions were used to refine and validate the predictive model (aims 1 and 2). Based on the final model, a decision support tool that can be used on paper or in a computer generated version, was created.

Theoretical Framework

Meleis' transitions theory (Meleis, 2010) guided the conceptualization of hospital to home health agency transition in the current study. The transitions theory also helped to identify the potentially relevant study variables. Several major components of the transitions theory were explored in this study (see Table 1 for transitions theory definitions and related study variables groups):

- The nature of the transition consists of three components:

  (1) Transition types- in this study, health/illness type of transition was captured by variables presenting patients' primary diagnosis and comorbid conditions; transitions of a situational type was approximated by variables related to the caregiver (e.g. caregiver availability and willingness to help); and developmental

transitions was captured by socio-demographic characteristics of the patient (e.g. working status, widowhood).

(2) Patterns of transitions in the current study were approximated by several personal and clinical variables. For example, variable that captures whether the patient was hospitalized in the past six months (and the frequency of hospitalizations) indicated if the nature of hospitalization is single or sequential.

(3) Properties of hospital home health agency transition included: transition awareness was approximated by variables indicating patients' ability to cope with their medical condition (e.g. the ability to learn and barriers to follow medication schedule); change and difference property of transitions was presented by variables related to changing clinical status of the patient, for example change between previous and current activities of daily living; time span of the hospital home health agency transition in this study was defined broadly as time between hospital discharge and first nursing visit.

- This study aimed to identify the most important factors associated with the patient's priority for the first nursing visit. Thus, transition conditions (facilitators and inhibitors) were the main group of variables that were presented in the patient case summaries. I elicited and summarized experts' knowledge on the personal (e.g. race, age, self-rated health), and community (e.g. caregiver availability or home accessibility) conditions of the transitions. A detailed description of each of the variables and their categorization according to the transitions theory is presented in Table 1.

- The major goal of this study was to create a decision support tool, or Nursing therapeutics according to Meleis (2010), assisting clinicians to identify patient's priority for the first nursing visit.
- The final component of the transitions theory is a Pattern of response. These patterns are often related to patient outcomes and were not directly measured or presented in this study. However, the experts used their best judgment to identify the effect of each of the variables on patient's priority.

Most of the variables presented in case summaries were categorized as personal or environmental transition conditions (that might either be facilitators or inhibitors). See Table 1 for a detailed description of the study variables names, descriptions and congruent components of the transitions theory.

In congruence with the second conceptual framework for the study, the Data Information Knowledge Wisdom conceptual model (American Nurses Association, 2008; Matney et al., 2011), patient data were organized into case summaries (providing information about patient condition). Case summaries were analyzed by the expert nurses to elicit patient priority for the first nursing visit and the researchers traced, extracted and summarized experts' knowledge in a form of a predictive tool (nursing therapeutics).

Case Summaries

The comprehensive case summaries for the present study originated from a larger ongoing study by Bowles and colleagues (R01- NR007674). This larger study aims to optimize post acute care referrals for patients discharged from hospitals. To accomplish this goal, Bowles and colleagues extracted approximately 4,000 de-identified case summaries drawn from the acute care electronic health record from the participating study sites. Study sites are members of a consortium of users of the same electronic health record. Previously, data use agreements were signed with each hospital site that clearly outline what data is collected, de-identified, the required data elements, and how it is protected and used. The study received approval by the expedited review by the Institutional Review Boards at the University of Pennsylvania and at each hospital (where the Institutional Review Boards were present).

Study Site: Three hospitals within the same health system were used in this study (University of Pennsylvania Healthcare System). Bowles and colleagues collaborated with the information technology departments of the hospitals to extract the data to generate the case summaries. In the hospitals, these data populated an Interdisciplinary Adult Patient Profile and an Assessment/Intervention flow-sheet within the Knowledge Based Charting software. The Interdisciplinary Adult Patient Profile is collected on all patients by the admitting nurse. The Interdisciplinary Adult Patient Profile contains baseline data on health and social factors useful to describe health status. Socio demographic patient information, such as date of birth, gender, and race were obtained from the hospitals' admission, discharge and transfer databases. The Assessment/Intervention flow-sheet is used for daily documentation and contains elements such as functional status, fall assessment, risk score for pressure ulcers (Braden score), patients' cognitive status, pain status, and nutrition information. The last instance of the Assessment/Intervention flow-sheet documentation was extracted for the study to capture patient status. Both the Adult Patient Profile and Assessment/Intervention flow-sheet were used to generate a comprehensive case summary presenting patients characteristics during the hospital stay. See exemplary discharge case summary in Figure 8. For the present study, the case summaries provide a comprehensive source of patient centered information, describing variables identified with the help of the Meleis transitions theory (Meleis, 2010).

Figure 8: Exemplar discharge case summary

Discharge summary #268

Sociodemographics

The patient is 70 years old, White, non-Hispanic/-Latino female. The patient is married, is retired and has a college education.

Hospital stay summary

The patient's **primary diagnosis** during hospitalization was: Osteoarthrosis, localized, not specified whether primary or secondary, lower leg.

Also, the patient has the following **co-morbidities** (divided by |): Mixed hyperlipidemia | Anemia, unspecified | Depressive disorder, not elsewhere classified | Unspecified essential hypertension | Esophageal reflux | Osteoporosis, unspecified. The following surgical procedures were indicated: Total knee replacement.

Following **medications** were indicated (divided by |): Aspirin Chewable Tablet, Chewable 81 mg, ORAL, DAILY | Celecoxib (. CeleBREX) Capsule 200 mg, ORAL, 2 times per day Stop After 14 Days Nurse Instructions: Start with pm dose the day of surgery. | Enoxaparin Injectable 20 mg (. LOVENOX Injectable 20 mg) 30 mg, SUBCUTANEOUS, Every 12 hours Indication: VTE Prophylaxis | Gabapentin (. NEURONTIN Oral) Capsule 300 mg, ORAL, ONCE Nurse Instructions: To be taken on arrival at SPU. Do not give if less than 1 hour before scheduled surgery. | Hydrochlorothiazide Tablet 25 mg, ORAL, Daily | Labetalol Tablet 100 mg, ORAL, 2 times per day | Multivitamin Tablet 1 tablet(s), ORAL, DAILY | OxyCODONE +

Acetaminophen 5 mg-325 mg (. PERCOCET-5) 2 tablet(s), ORAL, Every 4 hours, *PRN For Severe Pain (8-10) Nurse Instructions: Do not exceed 4 gm of acetaminophen per day | OxyCODONE SR (. OxyCONTIN) 10 mg, ORAL, Every 12 hours Nurse Instructions: Age < 75 years old

The patient indicated no problems in following the medication regimen.

The admission type was: elective. Inpatient stay was 3 days.

Health characteristics

The patient has the following vision conditions: decreased visual acuity; and the following hearing conditions: left hearing loss | right hearing loss.

The patient has the following wound types: erythema, at the following locations: vagina.

The patient has the following incision indicated: left knee incision, with the following appearances: no drainage | no redness | no swelling. The patient's pressure ulcer stage is: None.

The patient's level of consciousness level is: alert. The patient cognitive status is oriented x 4.

The patient is not at risk for falls. The patient's Braden score indicates that she/he is not at risk for developing pressure ulcers.

The patient has unintentionally lost >10 lbs in the last two months: no. He/she is at risk for eating poorly: no.

The patient self rated health is good.

In the past 6 months patient was admitted to hospital: Not at all, and visited ED: Not at all.

Functional status

Function	Status prior to hospitalization	Current status
Ambulation	Independent	assistive equipment
Transferring	Independent	assistive person
Toileting	Independent	assistive person
Bathing	Independent	assistive person
Dressing	Independent	assistive person
Eating	Independent	independent
Communicating	understands/communicates without difficulty	Missing
The patient reports a pain rating at rest of 4 (when measured on a scale of 0-10, with 0 being no pain)		

Individual and Psychosocial characteristics

The factors that influence patient's ability to learn are: none.

The patient was screened for depression using the following two questions: When asked how often, over past two weeks, the patient has been bothered by little interest or pleasure in doing things, the response was- not at all. When asked how often, over the past two weeks, the patient has been bothered by feeling down, depressed, or hopeless the response was- not at all.

In meeting health care needs, the patient has the following financial concerns: none. The patient has the following mental health conditions and symptoms: anxiety disorder.

Living environment

The patient lives in a(n) house, and lives with spouse. Characteristics and concerns about the physical layout and supportive elements of the patent's home are: stairs to enter home | stairs w/i home. The patient uses the following equipment: cane | raised or altered toilet | walker.

Caregiver characteristics The patient is the primary caregiver for his/her: no one.	
Caregiver questions	Responses
Someone is a available to assist patient if he/she is sick or disabled	Yes
The patient's caregiver/s is/are his/her	spouse
The caregiver is available on the following **days**	Weekends/Weekdays
Of these days, he/she is available at the following **times**	24/7
On these days and at these times, the caregiver is available	As needed
Willingness- the caregiver is	Willing to help
Ability- the caregiver is	Able to help
The caregiver's understanding of patient's medical care is described as	Adequate understanding

Pilot Study: Methods and Results

To inform the choice of the sample size and other aspects of statistical analysis, I conducted a pilot study with three Master's prepared transitional care nurse experts with more than 5 years of experience with transitional care. Nurses were given 20 randomly selected case summaries of patients that had been referred to home care services. The experts were asked to evaluate each case and provide a decision as to each patient's priority for the first home health nursing visit. The choices were: high, medium or low priority. In agreement with Bowles and colleagues work, the experts were instructed to make their decisions based solely on patient's clinical needs. Nurses were also asked to present a short rationale for their decisions and track their time to complete the summaries.

The results indicated that nurses categorized about 20% of the cases (3-4 out of 20) to the high priority category; 60% (12-14 cases) of the cases to the medium priority category; and 20% to the low priority category. The most frequent individual variables that influenced the timing decisions were: comorbid conditions (e.g. patients with insulin dependent diabetes and heart failure were identified as higher priority); medications (warfarin and insulin were common triggers to prioritize patients for care); functional status (completely dependent patients were identified as needing visits close to discharge); vision (patients with impaired vision were identified as needing visit close to discharge); mental health (patients with depression or anxiety were identified as needing visit close to discharge); social support (patients without appropriate social support were more likely to be categorized as needing visit close to discharge). Each expert spent about two hours examining the 20 case summaries.

Based on the results of the pilot and consultations with statistician (Dr. A. Hanlon), the most applicable method for this study is the ordinal logistic regression. In case of insufficient numbers in any one priority categories, the alternative analysis was the logistic regression.

Study Sample

Data were drawn for patients discharged alive between December 2012- June 2013. To assure representation of a variety of medical needs, the most common Medicare diagnostic related groups (DRGs) reported nationally were compared to the most common DRGs at the study sites (Center for Medicare & Medicaid Services, 2011). Bowles and colleagues found that the nationally representative DRGs are well represented in the study sites. To assure the accumulation of enough descriptive characteristics of the patient and the course of their hospitalization, patients with a length of stay < 2 days and those who died in hospitals were excluded.

Sample size: The total sample of case summaries includes 670 cases of patients referred to home health services. A power analysis to determine the number of cases needed for the proposed study was based on calculating the standard error associated with the Receiver Operating Characteristic Curve statistic (Pepe, 2004). Based on the pilot study data, I hypothesized that between 10% to 20% of the patients will be assigned to the first and last priority categories while the rest 60-80% will be assigned to the intermediate category. A sample size calculation showed that an ordinal logistic regression on continuous and nominal co-variates would require a sample size of 360 observations to achieve 80% power at a 0.05 significance level. Adjustment was also made for a possible association between the co-variates (R-Squared of 0.5). Inflating this for a “holdout” or validation sample of 30%, would require a total of about 520 subjects.

Institutional Review Board: The study was defined as an “exempted study” and received an IRB approval from the University of Pennsylvania.

Data Collection and Storage Procedures

To draw a sample for this study, I used all the case summaries of patients referred to home health services from the bigger data pool drawn by Bowles and colleagues (n=670). Of these, a randomly selected sub-sample was selected for the study.

Corresponding data files: I used the programming team working with Bowles and colleagues to build the web-based case summaries where the experts accessed them for judgment. To build the case summary, the required 63 data elements (such as patient's age, marital status, gender, etc.) were populated from the secure, de-identified research database. Similar to the work conducted by Bowles and colleagues, the programmers built a secure website that allowed password-protected access to the de-identified case summaries. Only the PI and the study team had access to the data. When experts were recruited and consented to participate in the study, they were be provided with a password to access the randomly assigned case summaries. Each expert evaluated 6 practice and 26 "real" cases.

The programmers also provided a data repository for capturing the expert responses. Each response was stored in the database. Upon the completion of the data collection, the responses were drawn from the centralized database for the data analysis as a comma separated value [CSV] file format. These files were then imported into the statistical software for the analysis. Only the PI and the research team had access to the file that was stored in a secure location within the protected School of Nursing Student drive.

Experts

For the purposes of this study, I recruited registered nurses with experience in transitional care. In general, transitional care models might be defined as range of time-limited services that complement primary care and are designed to ensure health care continuity and avoid preventable poor outcomes among at risk patient groups as they move from one level of care to another, among multiple providers and across settings (Naylor, Aiken, Kurtzman, Olds, & Hirschman, 2011). In the pilot work (Topaz et al., 2013), I found that home health nurses were often focused on their particular agency and did not have experience overseeing a continuum of care for the admitted patients. To overcome this barrier, this study used transitional care nurses who coordinate and manage patient transitions from hospital to home.

Purposeful sampling was used to recruit study participants referred to as experts throughout the dissertation. The inclusion criteria were: (1) experts should be a registered nurse with at least a Baccalaureate degree in nursing and (2) have at least five years of experience working as a transitional care nurse, care manager or care coordinator with responsibilities to assist in patient transfer from hospitals to home. Possible expert candidates were identified through advertisement in relevant professional networks, including the National Transitions of Care Coalition (NTOCC), the Omaha System listserv and other social media. Practitioners from four geographic areas of the US (East, West, Midwest, and South) were recruited to decrease the possible effects of geographical biases.

Judgment of the Case Summaries

Case summaries were posted on a secure website where each expert was able to log in to provide their judgments. Each expert judged the case summaries independently. First, experts were given six training cases to ensure that there are no issues with inter and intra-rater reliability (by comparing the average of responses). These six cases were purposefully selected by PI and the dissertation chair as representative of different priority levels (two cases per each priority category). Then, the experts proceeded to the second phase of the study where they evaluated an additional set of randomly drawn 26 “real” case summaries and provided decisions on the patient’s priority for the first home health visit. Experts were asked to indicate their priority for the first home health nursing visit. The priority was indicated on the sliding scale from 0-10, where one third of the cases were marked low priority (scores between 0-3.3); medium priority (scores between 3.3-6.6); and high priority (scores between 6.6-10). See Figure 9 for a screenshot of the scale. Experts were instructed to make their decisions based solely on patient’s clinical needs while ignoring local priority conventions or insurance barriers. A value of this approach is to build a system that identifies patients based on their needs for services.

After choosing the appropriate level of priority, experts were asked to revisit the case summary and indicate factors that led them to choose this particular category. These factors were the 63 variables presented in web-based case summaries (Table 1). In one third of the cases, experts were also asked to provide a short rationale for their decisions. This was done to provide an additional opportunity to better understand the priority decision-making processes and factors that affected those decisions.

Figure 9: Sliding priority scale for experts presented on the study website

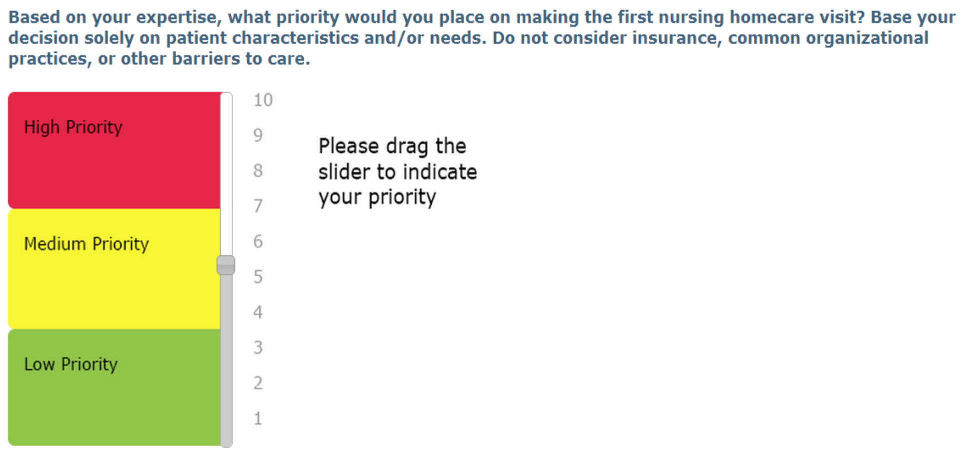


Table 1: Variables presented in case summaries and linkages to the transitions theory

Transition theory concepts	**Variables**	**Variable type**
Personal characteristics affecting transitions	Gender	Nominal (male/female)
	Marital status	Nominal (married/divorced/widowed etc.; 7 categories)
	Date of birth	Numeric date
	Race	Nominal (Asian/Black/White etc.; 8 categories)
	Ethnicity	Nominal (Hispanic/non- Hispanic origin)
	Educational level	Nominal (elementary/ high school/ college/ graduate school etc.; 7 categories)
	Employment status	Nominal (currently employed/ unemployed/ retired etc.)
	Date of admission	Numeric date
	Date of discharge	Numeric date
	Primary diagnosis	Nominal and ICD-9 code
	Type of admission	Nominal (emergency; ambulatory; transfer)
	Depression question 1: Question about feeling	Numeric (0- not at all to 3- nearly every day; 4 categories)

Transition theory concepts	Variables	Variable type
	little interest or pleasure during the past two weeks	
	Depression: Question about feeling down, depressed, or hopeless during the past two weeks	Numeric (0- not at all to 3- nearly every day; 4 categories)
	Patient provides primary care for	Nominal (children/ friend/ spouse etc.; 7 categories)
	Self-rated health (previous general health)	Nominal (excellent to poor, 5 categories)
	Healthcare utilization: hospital admissions in past 6 months	Nominal (not at all= 0 to more than 3 times; 4 categories)
	Healthcare utilization: emergency department visits in past 6 months	Nominal (not at all= 0 to more than 3 times; 4 categories)
	Living arrangements	Nominal (apartment/ house/ homeless etc. ; 13 categories)
	Equipment currently	Nominal (cane/ walker/wheel chair etc. ;

Transition theory concepts	Variables	Variable type
	used at home: yes/no and which equipment.	29 categories)
	Barriers to following a medication schedule	Nominal (none/ unable to afford medications/ unable to prepare and administer medications etc. ; 7 categories)
	ADL functional level current: ambulation	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: transfer	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: toileting	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: bathing	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: dressing	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: eating	Nominal (independent to completely dependent; 4 categories)
	ADL functional level current: communicate	Nominal (independent to completely dependent; 4 categories)
	Braden scale: total score	Numeric (scale of 6-23)

Transition theory concepts	Variables	Variable type
	Fall risk score calculation	Numeric (scale of 0-125)
	Pressure ulcer stage	Ordinal (stage 1 to 4)
	ADL functional level prior: ambulation	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: transfer	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: toileting	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: bathing	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: dressing	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: eating	Nominal (independent to completely dependent; 4 categories)
	ADL functional level prior: communicate	Nominal (independent to completely dependent; 4 categories)
	Co-morbid Conditions	Nominal and ICD code
	Cognitive/Perceptual/Neuro: Level of Consciousness	Nominal (alert to unresponsive; 11 categories)
	Diet tolerance	Nominal (good to no appetite; 8

Transition theory concepts	Variables	Variable type
		categories)
	Discharge medications	Nominal (medications names, dosage and administration)
	Wound location	Nominal (location on the body; 78 locations)
	Wound type	Nominal (from intact skin to pressure ulcer; 27 categories)
	Incision location	Nominal (location on the body; 78 locations)
	Incision appearance	Nominal (open/ close/ surgical wounds etc.; 14 categories)
	Factors that will Influence Ability to Learn	Nominal (from none to physical limitations; 11 categories)
	Mental health conditions/symptoms	Nominal (none/ anxiety/ depression etc.; 26 categories)
	Nutrition risk screen (weight loss and risk for eating poorly)	Nominal (yes or no)
	Cognitive/perceptual/neuro: orientation	Nominal (oriented X4 to disoriented; 4 categories)
	Pain assessment: pain	Nominal (scale of 0 to 10)

Transition theory concepts	Variables	Variable type
	scale number rest	
	Vision (eye conditions/symptoms)	Nominal (from no problems to blind; 28 categories)
	Financial concerns	Nominal (none to no insurance coverage; 8 categories)
	Hearing (ear conditions/symptoms)	Nominal (none to deaf; 12 categories)
Environmental characteristics affecting transitions	Equipment needed after discharge (home equipment needs)	Nominal (cane/ walker/wheel chair etc. ; 23 categories)
	Home accessibility	Nominal (no concerns to house is not wheelchair accessible; 11 categories)
	Lives with	Nominal (alone/ sibling/ spouse etc.; 11 categories)
	Caregiver availability: days	Nominal (weekends/ weekdays etc.; 5 categories)
	Caregiver availability: time	Nominal (daytime to all the time; 6 categories)
	Caregiver availability: assistance yes/no	Nominal (yes or no)
	Caregiver willingness to	Nominal (willing to unwilling to help; 4

Transition theory concepts	Variables	Variable type
	help	categories)
	Caregiver ability to help	Nominal (able to unable to help; 4 categories)
	Caregiver availability: frequency	Nominal (whenever needed to never; 7 responses)
	Caregiver availability: relationship	Nominal (child to significant other; 13 categories)
	Caregiver understanding	Nominal (unable to understand to full understating; 7 categories)

Statistical Analysis

Statistical procedures applied in this study can be broadly divided into three central steps: 1. Examination of the optimal variable categorization; 2. Selection of variables associated with the priority for the first home health nursing visit; and 3. Construction and validation of the best predictive model imitating experts' decisions on patient priority (see Figure 10 for an overview of the process). Before conducting any analysis, a holdout sample (further referred as the testing dataset) with one-third of the cases was withheld from the full dataset for further model validation purposes. Description of the methods used in each of the steps follows:

STEP 1: Examination of the optimal variable categorization (Aim 1).

The first step was focused on examining variables to populate further statistical analysis and modeling. Several variables included in this study were very granular, i.e. categorical variables with many categories. For example, patients in this study had between 0-37 comorbid conditions captured by individual ICD-9 (9th International Classification of Diseases) codes. Working with categorical variables, the rule of thumb was that categorical variables should be collapsed to ensure sufficient numbers (>5%) in any one category (Hosmer, Lemeshow, & Sturdivant, 2013). One approach to working with codes from standardized terminologies, such as ICD-9, is to use existing classification systems to up-code individual codes to higher-level category.

In this study, I used a tool developed by the Healthcare Cost and Utilization Project (HCUP) to accomplish that. HCUP was established and funded through the U.S. Health & Human Services (HHS) and the Agency for Healthcare Research and Quality (AHRQ) and it constructs and maintains a diverse range of tools for terminology work

(Agency for Healthcare Research and Quality, 2014). Using the statistical software (STATA) with HCUP application, I generated first, second and third level categorization for each of the primary diagnoses, comorbid conditions and family/personal history variables. For example, a comorbid condition "Congestive heart failure, unspecified" (ICD9 code) was classified as "Diseases of the circulatory system" at level one (highest level); "Diseases of the heart" level two; and "Congestive heart failure; nonhypertensive [108.]" level three. The HCUP tool was used to generate categories for the primary diagnosis, comorbid conditions, and family and personal history variables.

Procedures were an additional variable represented by ICD-9 codes. Here again HCUP software was used to generate higher level procedure categories (Agency for Healthcare Research and Quality, 2014). In general, procedures were divided into four classes (based on HCUP classification): minor and major therapeutic procedures and minor and major diagnostic procedures.

An additional granular variable were the prescribed medications. However, "raw" medication data in the data-file were presented as long description of the medication with its dosage, times and frequent additional information, for example "Hydralazine 50 Mg Tablet. 1 Tab(S) Orally 2 Times a Day X 30 Days". In order to make medications usable for the analysis, medication groupings based on their pharmacological action were created. To accomplish that, I used the Veteran Administration (VA) drug classes, which is one of the most thoroughly developed and commonly used drug group classifications (U.S. Department of Veteran Services, 2014). Some of the benefits of using this classification are: 1) open public access to the terminology and 2) inclusion in the most commonly used larger pharmacological ontology (RxNorm, which in turn grants inclusion in many other medical terminologies, such as the Unified Medical Language System, the UMLS) (U.S. Department of Veteran Services, 2014).

The first step in generating the VA drug classes was “cleaning” the long medication descriptions to include only generic drug names. Recently, several natural language processing systems enabling extraction of a medication name from unstructured medical texts were developed. Because of the ease of use, open access and through development, the most applicable for this study was using the RxMix, an application program interface developed and maintained by the National Library of Medicine (National Institute of Health & National Library of Medicine, 2014). Other researchers have successfully used this interface work with unstructured medication data (Peters, Mortensen, Nguyen, & Bodenreider, 2013) and here I followed a process outlined by Olson and colleagues in their recent study on automation of a high risk medication regime algorithm in a home health care population (Olson, Dierich, & Westra, 2014). Simply put, I took the unique, de-identified medication names from the data file and applied RxMix to analyze it. In turn, RxMix applied natural language processing algorithm to: 1. extract the medication name from each line of an unstructured data and then 2. search for the VA drug class for each medication. Afterwards, each unique medication and VA drug class matches were manually evaluated by the PI.

Other variable subsets and categorization choices were performed based on a combination of frequency tables (to identify categories satisfying the rule of thumb) and data mining. For example, the optimal categorization for functional status variables was chosen based on a data mining procedure called feature selection. WEKA- a software package for data mining- was used for this analysis (Witten, Frank, & Hall, 2011). In general, feature selection algorithms evaluate the worth of a subset of variables by considering the individual predictive ability of each variable along with the degree of redundancy between them. Several methodological approaches, which differ in the way they arrive to the final variable subset, exist. As often accepted in data mining, I iteratively used several methods for feature selection (Information Gain, Gain Ration, Correlation Feature Selection and Chi-square evaluator) to identify the best average variable categorization and subset choices (Witten et al., 2011). For example, dichotomous (no limitations vs. some/major limitations in mobility) and three categorical patient's mobility status categorization (no limitations, some limitations or major limitations in mobility) were compared, and a subset with the highest association with the outcome was chosen for use in the final models.

STEP 2: Selecting variables associated with priority for the first home health nursing visit (Aim 1).

a. First, an analysis of general sample characteristics and experts' responses using bivariate comparisons and distributions by home health visit priority category was performed.
b. Then, I confirmed the applicability of the variable categorizations (conducted in Step 1) and validated the results of the bivariate comparisons (conducted in Step 2.a) by applying two statistical techniques: 1. Variable feature selection (Information Gain, Gain Ration, Correlation Feature Selection and Chi-square evaluator) and 2. Bootstrap variable selection method (the method draws random samples form the data to validate the choice of variables in stepwise backward elimination procedure) (Hosmer et al., 2013). **Appendix II** provides a detailed description of the data mining and other statistical procedures implemented.

c. Interactions between independent variables were also examined to identify possible interaction terms for inclusion in the final model.
d. Finally, experts' rationale descriptions (that were required in one third of the case summaries) were used to perform qualitative validation of the variables identified for the final models.

STEP 3: Constructing and validating the best predictive model imitating experts' decisions on patient's priority (Aim 2).

a. Construction and validation of a predictive model: a subset of variables identified in Step 2 (a-c) was used to develop the final model. The candidate variables and interaction terms were put in the forward selection logistic model in STATA (Hosmer et al., 2013) and only significant variables ($p<.15$) were retained in the model. In following iterations, model's predictive ability, as reflected by the the receiver operator curve statistic (ROC), was gradually improved by removing the least significant variables (Hosmer et al., 2013). Estimation of the model's predictive ability was performed on the testing holdout sample that consisted of a third of the cases from the original full dataset. The optimal cut-off score for the probability to be assigned to the low/medium or high priority categories was identified. Because of the clinical importance of accurately identifying the high priority patients, the optimal cut-off score was based on increasing the sensitivity of the model while keeping specificity in acceptable ranges. Table 15 presents step-by-step iterations that were implemented to achieve the final model.
b. Model diagnostics were then performed to estimate and possibly improve the model's fit.

c. Experts' model validation: the final model was discussed with a convenience sample of three experts for validation.

d. Other validation: model's patient categorization as low/medium or high priority was compared against data on patient rehospitalizations (up to 60-day rehospitalizations).

CHAPTER 4: RESULTS

Case Summaries

Overall, the sample included 670 case summaries of patients referred to home health. Previously, Bowles and colleagues completed the data cleaning work on the case summaries for consistency throughout (Bowles et al., 2013). In addition, each case summary was thoroughly read for clinical consistency: a quarter (n=141) of the case summaries were reviewed by Bowles's study team and the PI , the remaining were reviewed by the PI. In general, the changes that were made included: (1) removing exact duplications in terms of medications and comorbidities (i.e. when the same comorbidity was mentioned twice) and (2) making sure that information is presented consistently. For example, I had two variables capturing possible mental health issues, namely "comorbid condition" and "mental health status". I made sure that the conditions indicated by both variables are consistent, i.e. if patient had a mental condition of schizophrenia in the list of mental health conditions; this condition was included in the list of comorbid conditions. Only few cases needed corrections/changes (about 5% of the summaries) that were approved by the dissertation chair.

Experts and Data Collection

Twenty four experts who complied with the inclusion criteria (1. were a registered nurse with at least a Baccalaureate degree in nursing and 2. had at least five years of experience working as a transitional care nurse, care manager or care coordinator with responsibilities to assist in patient transfer from hospitals to home) responded to the call for participation. Four experts were lost due to attrition: one expert was unable to participate due to personal reasons (spouse illness) and three candidates did not complete the training phase and did not respond to further emails from the investigator. The 20 remaining experts who completed the study were from four geographic areas in the U.S. (Midwest – 6 experts, North-East- 7 experts, South- 4 experts, West- 3 experts) and served in a variety of clinical positions ranging from directors of care management to field nurses in transitional care programs. Eight experts were Certified Case Managers (CCM) and six had Master level degrees in nursing (Certified Nurse Practitioner and Master of Nursing Science).

At the first phase of the study, the experts were asked to complete six training cases that were purposefully selected by the study PI and the dissertation adviser as representing the three possible levels of priority for the first home health nursing visit. All of the experts were provided with the same case summaries. Before accessing the cases summaries, experts were required to watch a brief (8 minutes) software-video tutorial to introduce the case summary structure and website functionalities. The tutorial was based on our validated methodology for creating short software tutorials for health practitioners (Topaz, Rao, Masterson Creber, & Bowles, 2013).

All the experts who completed the assigned training case summaries were finished within one week. I compared each expert's response to the average of other experts' responses to identify outliers or patterns of disagreement with the majority of experts. Overall, although experts' responses varied, there was no individual pattern of systematically assigning a higher/lower score to a case summary compared to an average response. I also examined the number and consistency of the selected factors between the experts. Again, I did not observe a consistent pattern of selecting a few/majority of the factors or individual's systematic deviation from a mean response.

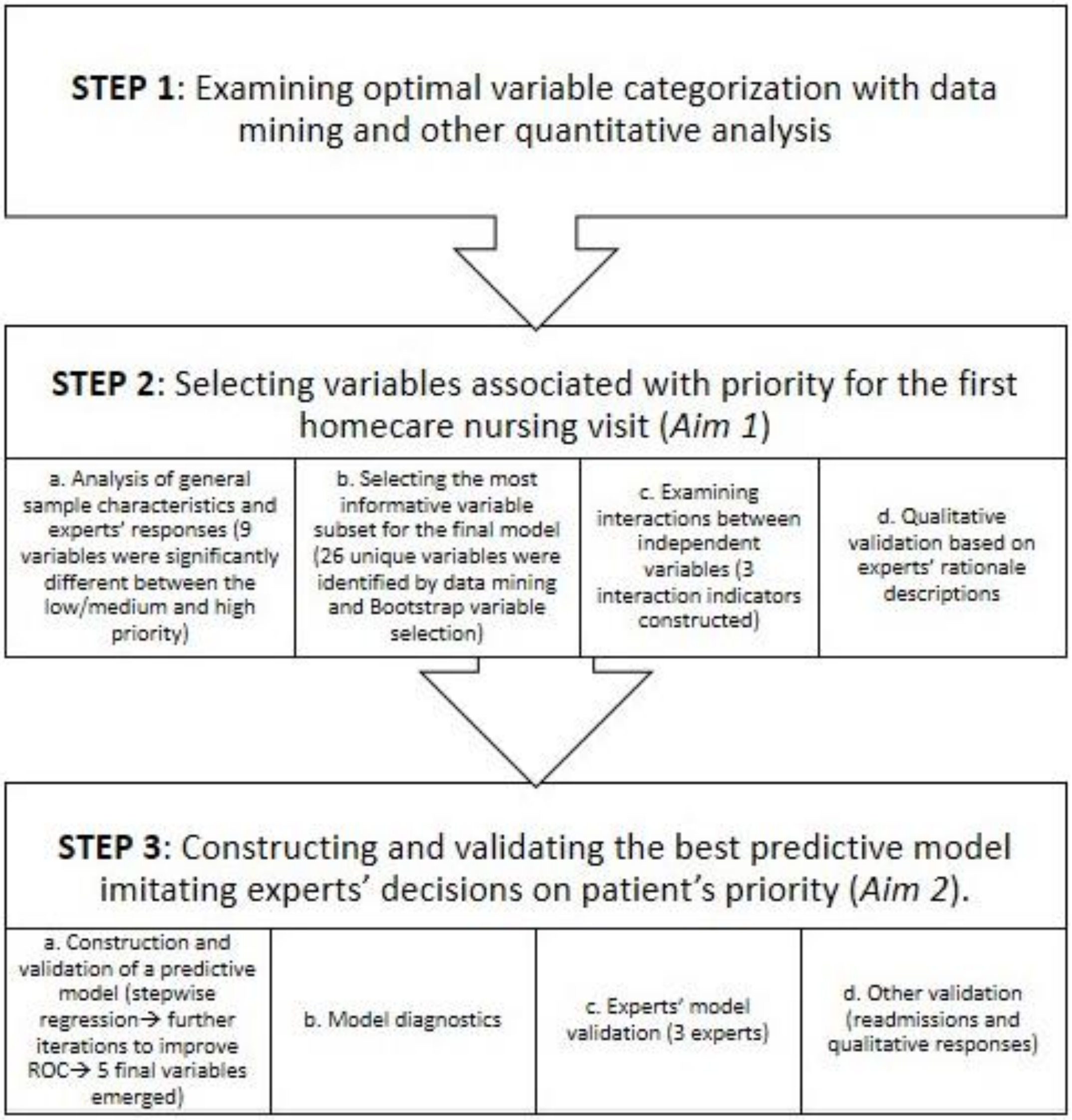
During the training phase, experts were also asked to provide comments and suggestions on the website usability or any other issues. One repeated comment was about adding a prescription date to the medication information. Experts felt that in addition to the presented dosage and route information, date of prescription might help them understand if the medication is new or a routine for the patient. Unfortunately, this information was not included in the original data and was not provided. In general, the experts found the website (developed by Bowles and here team and the software vendor) to be very user friendly and had favorable comments on the way the data were presented. The sliding priority scale (Figure 9) also worked well and no concerns were raised on the topic.

After the successful completion of the training phase, each expert was assigned 26 randomly selected case summaries and invited to complete them within three weeks. All the experts completed their cases and data collection was completed during April 2014. Experts were provided with financial compensation for participation.

Data Analysis

In general, before conducting any analysis, a holdout sample with one-third (n=176) of the cases was withheld from the 519 case summaries reviewed by experts. All the analyses were conducted on the training dataset of 343 case summaries- those results are reported in the figures and tables throughout the manuscript. Several statistical approaches to selecting variables and variable subsets for the final model were utilized. Figure 10 overviews the central steps of the statistical analysis in this study.

Figure 10: Statistical analysis procedure outline



STEP 1: Examining optimal variable categorization with data mining and other quantitative analysis (Aim 1).

Since comorbidities and primary diagnoses were often selected by the experts as variables associated with the outcome, one of the first tasks was to examine this data. First, I used a statistical software (STATA) with HCUP application to generate first, second and third level categorization for each of the primary diagnoses, comorbid conditions and family/personal history variables (see more details in Methods section, Step 1). Clinically, third level of ICD-9 categorization was preferable: it provided more general categories than individual ICD-9 codes but was more specific than the first or second level disease categories, which can possibly include up to a dozen different individual conditions. Because of those clinical considerations and relatively high frequencies of the third level comorbid conditions (Table 2), I decided to use the third level in the final models.

Table 2 presents the most common comorbidity categories selected by the experts (level three). Table 2 also shows how many comorbid conditions of a certain type were present in the sample. For instance, at the third level of ICD-9 hierarchy, the most frequently selected condition was the “Congestive heart failure; nonhypertensive [108.]”- it was selected as significantly affecting experts’ priority choice 88 times, which comprises 41.5% of the frequency this condition appears in the full training dataset. Overall, 495 comorbid conditions were selected by experts. Table 2 indicates that the most frequent categories selected by experts were: congestive heart failure, nonhypertensive; chronic kidney disease; cardiac dysrhythmias; coronary atherosclerosis and other hear essential hypertension; acute and unspecified renal failure, etc.

Table 2: The most common comorbid conditions (level three) from experts' responses and overall training sample

Frequency ranking§	Comorbid condition name	Frequency §	% out of total§	% out of total comorbidities in this category	Ranking (full sample)	Freq. (full sample)*	Percent (full sample)
1	Congestive heart failure; nonhypertensive	88	8.1	41.5	3	212	4.6
2	Chronic kidney disease [158.]	62	5.7	39.2	6	158	3.4
3	Cardiac dysrhythmias [106.]	50	4.6	26.9	4	186	4
4	Coronary atherosclerosis and other heart diseases	42	3.8	12.7	1	332	7.2
5	Essential hypertension [98.]	42	3.8	16.8	2	250	5.4
6	Acute and unspecified renal failure	36	3.3	43.4	13	83	1.8
7	Other aftercare [257.] (e.g. continuous use of anticoagulants)	35	3.2	21	5	167	3.6
8	Complications of surgical procedures	31	2.8	29.8	10	104	2.2
9	Depressive disorders [6572]	28	2.5	48.3	17	58	1.2
10	Hypertension with complications	28	2.5	23.9	8	117	2.5

Frequency ranking§	Comorbid condition name	Frequency §	% out of total§	% out of total comorbidities in this category	Ranking (full sample)	Freq. (full sample)*	Percent (full sample)
11	Deficiency and other anemia [59.]	24	2.2	16.8	7	143	3.1
12	Obesity	20	1.8	23.8	12	84	1.8
13	Decubitus ulcer	19	1.7	79.2	49	24	0.5
14	Other and unspecified metabolic; nutrition issues	19	1.7	51.4	37	37	0.8
15	Other liver diseases [151.]	18	1.6	41.9	27	43	0.9
16	Chronic airway obstruction	16	1.4	32	23	50	1.1
17	Pulmonary heart disease [103.]	16	1.4	30.8	21	52	1.1
18	Other nervous system symptoms and disorders	15	1.3	34.9	28	43	0.9
19	Other and unspecified gastrointestinal disorders	14	1.2	23	16	61	1.3
20	Heart valve disorders [96.]	13	1.2	14.9	11	87	1.8
21	Codes related to substance-related disorders	12	1.1	23.1	19	52	1.1
22	Other and unspecified lower respiratory disorders	12	1.1	23.5	22	51	1.1

Frequency ranking§	Comorbid condition name	Frequency §	% out of total§	% out of total comorbidities in this category	Ranking (full sample)	Freq. (full sample)*	Percent (full sample)
23	Diabetes with neurological manifestation	11	1.01	57.9	61	19	0.4
24	Esophageal disorders [138.]	10	0.9	9.3	9	107	2.3
25	Other fluid and electrolyte disorders	10	0.9	21.7	25	46	1

§ Experts' choices *Overall count of comorbid conditions is used rather than a unique count per patient. Thus, numbers might differ from those presented in sample description where conditions uniquely identify each case summary.

Frequencies of primary diagnoses are presented in Table 3. When considering what levels of granularity for the primary diagnoses categories should be included in the final analysis to satisfy the rule of thumb (categorical variables should be collapsed to ensure sufficient numbers >5% in any one category), I identified that only codes of level two or higher could be used. For example, even at the second level, the third most frequent condition was “Spondylosis; intervertebral disc disorders” and it appeared in only 24 case summaries (Table 3). The decision was made to retain the most common primary diagnoses satisfying the rule of thumb at the second level for examination in the final models.

Table 3: The most common primary diagnosis (levels 1 and 2) categories from experts' responses and overall training sample

Frequency ranking§	**Primary diagnosis**	**Frequency§**	**Percent§**	**Frequency ranking§**	**Freq. (full sample)**	**Percent (full sample)**
			Level 1			
1	Diseases of the circulatory system	45	23.6	59.2	76	22.1
2	Neoplasms	31	16.3	57.4	54	15.7
3	Injury and poisoning	24	12.6	68.6	35	10.2
4	Diseases of the musculoskeletal system	22	11.5	48.9	45	13.1
5	Infectious and parasitic diseases	13	6.8	76.5	17	4.9
6	Diseases of the digestive system	10	5.2	34.5	29	8.4
7	Diseases of the genitourinary system	9	4.7	50	18	5.2
8	Diseases of the respiratory	9	4.7	52.9	17	4.9

Frequency ranking§	Primary diagnosis	Frequency§	Percent§	Frequency ranking§	Freq. (full sample)	Percent (full sample)
	system					
9	Endocrine; nutritional; and metabolic diseases	9	4.7	45	20	5.8
10	Diseases of the skin and subcutaneous tissues	6	3.1	85.7	7	2.0
11	Symptoms; signs; and ill-defined conditions	6	3.1	75	8	2.3
Level 2						
1	Diseases of the heart	30	15.9	56.6	53	15.5
2	Complications	16	8.5	69.6	23	6.7
3	Spondylosis; intervertebral disc disorders	12	6.3	50	24	7
4	Bacterial infection	10	5.3	83.3	12	3.5
5	Diseases of the urinary system	9	4.7	56.3	16	4.7
6	Diseases of arteries; arterioles	8	4.2	66.7	12	3.5
7	Non-traumatic joint disorders	8	4.2	47.1	17	5
8	Other gastrointestinal cancer	7	3.7	70	10	2.9
9	Fluid and electrolyte disorders [55.]	6	3.1	60	10	2.9
10	Cancer of bronchus; lung [19.]	5	2.6	71.4	7	2

Frequency ranking§	Primary diagnosis	Frequency§	Percent§	Frequency ranking§	Freq. (full sample)	Percent (full sample)
11	Fractures	5	2.6	83.3	6	1.7
12	Skin and subcutaneous tissue infections	5	2.6	83.3	6	1.7
13	Symptoms; signs; and ill-defined conditions	5	2.6	71.4	7	2
14	Abdominal hernia [143.]	4	2.1	50	8	2.3

Freq. = Frequency; § Experts' choices.

Similarly, experts' choices and overall data representing family/personal history codes were examined. The frequencies for the family history variables were quite small even at the second level (see Table 4). Moreover, those factors were infrequently selected by the experts. For example, even a broad category of "Neoplasms" was selected only in 20.3% of the cases indicating this type of history. Thus, the decision was made to examine the effect of those variables at the second and first level with the possible option to examine a more granular third level, if needed.

Table 4: The most common personal/family history categories (HCUP, level one) from experts' responses and overall training sample (this variable has only few/infrequent categories at the second level- first level was kept with broader categories)

Personal/family history condition	Freq. §	Percent§	Frequency ranking§	Freq. (full sample)	Percent (full sample)
Diseases of the circulatory system	38	28.3	52.1	73	14.8
Mental illness	30	22.3	28.8	104	21.1
Neoplasms	30	22.3	20.3	148	30.1
Injury and poisoning	2	1.4	66.7	3	0.2
Symptoms; signs; and ill-defined conditions	2	1.4	3.3	61	12.4

Diseases of the nervous system	1	0.7	100.0	1	0.2
Diseases of the respiratory system	1	0.7	100.0	1	0.2

Freq. = Frequency; § Experts' choices.

Granular procedures levels in the dataset had quite small frequencies: for example, the third most common procedure "Central venous catheter placement with guidance" was performed only 20 times (Table 5). In the dataset, procedures were relatively frequent: there were 282 major therapeutic, 169 minor therapeutic and 141 minor diagnostic procedures performed (Table 6). Experts selected relatively high number of major/minor therapeutic and minor diagnostic procedures. Those three categories of procedures were kept for the final analysis and major diagnostic procedure category was excluded because of the small frequency (n=10).

Table 5: The most common procedures from expert's responses and overall training sample.

Procedure name	**Freq. §**	**Percent**	**Frequency ranking §**	**Freq. (full sample)**	**Percent (full sample)**
Transfusion of packed cells	11	3.1	23.9	46	5.3
Central venous catheter placement with guidance	8	2.3	40	20	2.3
Other exploration and decompression of wound	8	2.3	57.1	14	1.6
Total knee replacement	8	2.3	26.7	30	3.4
Open and other replacement of aortic valve	6	1.7	35.3	17	1.9
Total hip replacement	6	1.7	60	10	1.1
Fusion or refusion of 2-3 vertebrae	5	1.4	83.3	6	0.7
Other kidney transplantation	5	1.4	83.3	6	0.7
Other incision with drainage of skin	4	1.1	100	4	0.4
Other open incisional hernia repair	4	1.1	66.7	6	0.7
Percutaneous abdominal drainage	4	1.1	44.4	9	1

Freq. = Frequency; § Experts' choices.

Table 6: Most common procedure classes categories expert's responses and overall training sample

Procedure class name	Freq. §	Percent	Freq. ranking§	Freq. (full sample)	Percent (full sample)
Major Therapeutic	146	48.3	51.8	282	40.1
Minor Therapeutic	98	32.4	36.4	269	38.3
Minor Diagnostic	54	17.8	38.3	141	20.0
Major Diagnostic	4	1.3	40.0	10	1.4

Freq. = Frequency; § Experts' choices.

Medications were another category that was relatively frequently selected by the experts. Overall, the sample included 2728 medications and 12.8% of them (n=350) were selected by the experts. To classify medications into drug classes, RxMix (an application program interface developed and maintained by the National Library of Medicine described in the Methods Section, step 1) was applied (National Institute of Health & National Library of Medicine, 2014). Overall, RxMix recognized about 85% of the medication names and for those that were not recognized, a manual search in the VA drug class file was performed. All the common medications were assigned a VA class. Table 7 presents the most common drug classes chosen by experts and their overall presence in the full study sample. Seven most common drug classes satisfying the rule of thumb were included in the final models.

Table 7: Most common medication classes (VA drug class) categories from experts' responses and overall training sample

VA drug class	Freq. (experts' choices)	Percent (experts' choices)	Frequency ranking (experts' choices)	Freq. (full sample)	Percent (full sample)
Opioid analgesics	56	16.2	25.3	221	8.1
Anticoagulants	50	14.5	19.8	252	9.1
Loop diuretics	22	6.4	27.2	81	2.9
Insulin	19	5.5	19.8	96	3.5
Beta blockers/related	15	4.3	9.1	165	6
Nonsalicylate NSAIDs, antirheumatic	12	3.4	6.9	175	6.3
Stimulant laxatives	12	3.4	9.0	134	4.8
Antiarrhythmic	9	2.6	27.3	33	1.2
Oral hypoglycemic agents, oral	9	2.6	21.4	42	1.5
Thyroid supplements	8	2.3	15.4	52	1.9
Ace inhibitors	7	2	8.4	83	3
Antiasthma, other	7	2	14.9	47	1.7
Cephalosporin 1st generation	7	2	38.9	18	0.6
Benzodiazepine derivative sedatives	6	1.7	13.6	44	1.6
Skeletal muscle relaxants	6	1.7	28.6	21	0.7

A combination of quantitative analysis and data mining was used to identify the most informative functional status categorization. Our data included three types of functional status categories- past functional status, present functional status and change in functional status. Originally, past and present functional status variables were represented using five categories (from “independent” to “completely dependent”). However, the numbers of responses were quite small for many categories and the decision was made to try different re-categorization until the best fit in terms of the effect on the outcome variable is found. Examining the frequencies of experts’ choices of the past functional status variables, it was evident that those variables were rarely selected, if at all. This indicated that past functional status is not an optimal variable to use in the final models and it was left out of the further analysis. Change in functional status was indicated as improvement, decline or no change. Most often, the decline was selected by the experts (see Table 11).

One issue with current functional status and change variables was the collinearity - the experts tended to select several functional status variables together. To avoid the possible issues related to high between-variable correlation in the final models, I generated an index variable indicating a number of functional status limitations for each case summary. This functional status index was used in combination with other variables or separately, as discussed below.

As commonly accepted in data mining analysis, I iteratively used several methods for feature selection (Information Gain, Gain Ration and Chi-square evaluator) to identify the optimal subset (Witten et al., 2011). An additional method that pays more attention to interactions between the variables, the Correlation Feature Selection (CFS), was also applied using different search algorithms (CFS results not presented due to difference in output structure). Table 8 presents the relative ranking of each of the variable subsets as well as the ranking of each individual variable within each subset. The results suggest that the most informative subset included the original, five categorical current functional status variables, followed by the dichotomous variables, 3-categorical, and lastly the functional status change variables. However, the original five categorical functional status variables did not satisfy the rule of thumb because of the small category frequencies. Therefore, using dichotomous variables seemed like an optimal option. CFS results confirmed the subset choice.

Table 8: Summary of rankings (representing relative explanatory contribution of the individual variables to explaining the outcome variable) of the different functional status subsets with relative ranking of each of the subsets (last column). The relative ranking by subset is based on the average of individual variable ranking scores. The most informative subset includes the five-categorical variables, then dichotomous, three-categorical, and lastly the functional status change variables.

Variable name	**Info-gain ranking**	**Gain-ratio ranking**	**Chi-square ranking**	**Individual variable ranking in subset**	**Relative ranking by subset**
Toileting current	1	8	1	1	1
Transfer current	2	12	2	2	
Bathing current	7	14	8	3	
Ambulation current	4	21	6	4	
Dressing current	10	16	10	5	
Communication current	22	1	22	6	
Eating current	19	6	20	7	
Toileting current (dichotomous)	5	3	4	1	2
Transfer current (dichotomous)	8	4	7	2	
Bathing current (dichotomous)	14	10	14	3	
Dressing current (dichotomous)	17	13	17	4	
Ambulation current (dichotomous)	18	17	18	5	

Variable name	Info-gain ranking	Gain-ratio ranking	Chi-square ranking	Individual variable ranking in subset	Relative ranking by subset
Communicate current (dichotomous)	27	2	27	6	
Eating current (dichotomous)	24	18	24	7	
Toileting current (3 cat.)	3	7	3	1	
Transfer current (3 cat.)	6	9	5	2	
Bathing current (3 cat.)	11	15	11	3	
Dressing current (3 cat.)	16	19	16	4	3
Ambulation current (3 cat.)	15	24	15	5	
Communicate current (3 cat.)	26	5	26	6	
Eating current (3 cat.)	23	23	23	7	
Toileting changed	9	11	9	1	
Bathing changed	12	20	12	2	
Transfer changed	13	22	13	3	
Dressing changed	20	25	19	4	4
Ambulation changed	21	28	21	5	
Eating changed	25	27	25	6	
Communicate changed	28	26	28	7	

Cat.= categories

To confirm variable choices of functional status and comorbid conditions categorization, I iteratively implemented 10 different models that included slightly different variable subsets combinations. For example, the first variable subset included all the possible categorizations of the functional status, i.e. functional status dichotomous, three-categorical, change indicators, and functional deficits count. The variable subsets were iteratively removed and added back to assess the change in the model's predictive ability measured in terms of ROC and model's accuracy (with 10 fold validation). The five different data mining approaches applied to each model were:

decision trees (J48 and random tree); Naïve Bayes; logistic regression classifier; and rules (PART classifier) (Witten et al., 2011). Overall, the results indicated that the best predictive models were achieved with dataset that included dichotomous functional status variables + most frequently selected by experts change variables (ambulation change & toileting change). The predictive ability of the dataset improved when third level comorbid conditions were added- the final model had an average of 65.2 ROC and accuracy of 63%. See Table 9 for more details.

Table 9: Selecting the most informative subset of functional status and status change variables for final regression models. Here full models including all the possible predictor variables were used first, then only a subset of functional status and functional status change variables were kept iteratively. Each model was evaluated with five different data mining techniques (Trees: J48 and random tree; Naïve Bayes; Logistic regression classifier; Rules: PART classifier). The comparative subset ranking was based on the average of individual variable ranking scores. Overall accuracy of the models is presented with ROC value to identify the most informative variable subset.

Variables included	**Method**	**ROC (%)**	**Average ROC of the classifiers (%, SD)**	**Comparative subset ranking (based on accuracy + ROC)**
Iteration 1: Full model (functional status dichotomous, 3 categorical , change indicators, functional deficits count)	J48	60	59.6 (3.26)	10
	Random tree	60		
	NaiveBayes	65		
	Logisitc	58		
	Rules(PART)	55		
Iteration 2: Model with current functional status variables only (no change etc.)	J48	65	64.2 (2.3)	3
	Random tree	61		
	NaiveBayes	66		
	Logisitc	67		
	Rules(PART)	62		
Iteration 3: Model with 3	J48	65	63.8 (2.26)	5

Variables included	**Method**	**ROC (%)**	**Average ROC of the classifiers (%, SD)**	**Comparative subset ranking (based on accuracy + ROC)**
category functional status variables only (no change etc.)	Random tree	59		
	NaiveBayes	67		
	Logisitc	65		
	Rules(PART)	63		
Iteration 4: Model with dichotomous functional status variables only (no change etc.)	J48	66	64.8 (2.31)	4
	Random tree	62		
	NaiveBayes	65		
	Logisitc	66		
	Rules(PART)	65		
Iteration 5: Model with count of limitations functional status variables only (no change etc.)	J48	65	64 (2.72)	6
	Random tree	58		
	NaiveBayes	67		
	Logisitc	66		
	Rules(PART)	64		
Iteration 6: Model with dichotomous functional status variables + all functional status change variables	J48	62	61.8 (1.47)	8
	Random tree	58		
	NaiveBayes	67		
	Logisitc	64		
	Rules(PART)	58		
Iteration 7: Model with count of limitations functional status + most important change variables only (ambulation_change & toileting_change)	J48	61	62.6 (3.16)	7
	Random tree	61		
	NaiveBayes	69		
	Logisitc	61		
	Rules(PART)	61		
Iteration 8: Model with dichotomous functional status variables + most	J48	63	64.8 (3.16)	2
	Random tree	63		

Variables included	Method	ROC (%)	Average ROC of the classifiers (%, SD)	Comparative subset ranking (based on accuracy + ROC)
important change variables only (ambulation_change & toileting_change)	NaiveBayes	68		
	Logisitc	66		
	Rules(PART)	64		
Iteration 9: Model with dichotomous functional status variables+ most important change variables (ambulation_change & toileting_change)+ 2nd level comorbid only	J48	59	60.2 (1.16)	9
	Random tree	60		
	NaiveBayes	62		
	Logisitc	59		
	Rules(PART)	61		
Iteration 10: Model with dichotomous functional status variables + most important change variables (Ambulation changed & Toileting changed)+ 3rd level comorbid only	J48	63	65.2 (2.27)	1
	Random tree	65		
	NaiveBayes	69		
	Logisitc	66		
	Rules(PART)	63		

STEP 2: Selecting variables associated with priority for the first home health nursing visit (Aim 1).

a. Analysis of general sample characteristics and experts' responses

In the overall sample of 519 case summaries, the distribution of the outcome was: 47 (9.1%) low home health first nursing visit priority; 222 (42.8%) medium home health first nursing visit priority; and 250 (48.1%) high home health first nursing visit priority. When randomly split, the sample was supposed to include only 31 low priority patients (2/3 of the group) in the training and 16 (1/3 of the group) in the testing datasets. Those small numbers did not leave us with enough statistical power to conduct the analysis thus it was decided to dichotomize the outcome into the meaningful groups of low/medium vs. high priority. Since the analysis was initially powered for a more resource demanding ordinal model, I had sufficient power to conduct logistic regression analysis.

Table 10 presents the overall distribution of socio-demographic and clinical characteristics of the training sample. In general, the average age was 69.7 (SD=9.5); predominantly White (63.9%); half of the sample were male (51%); 51.3% were married; most of the participants had high school or lower levels of education (61.5%); and only fifth (20.5%) were partially or full time employed. From the clinical perspective, participants had 11.5 (SD=5.6) comorbid conditions, took 11.4 (SD=5) medications and were hospitalized for an average of 5.5 (SD=3.8) days. 69% were admitted for an emergency reason. The most common reasons for admission were diseases of heart (15.8%); complications (e.g. infections after surgery, 6.8%) and urinary problems (4.8%). The most common comorbid conditions included: hypertension (6.2% of the overall number of comorbid conditions); cardiac artery diseases (4.3%); dysrhythmias (4.1%); long use of anticoagulants (3.7%); and CHF (3.3%). Overall, 18 most common comorbidities were used for the final models (Table 10).

About half of the patients have undergone either major (47.8%) or minor (46.6%) therapeutic procedure. Third of the patients had personal or family history of either mental health conditions or neoplasms. The most common medications were anticoagulants (56%), opioids (53.6%), NSAIDs (49.1%), beta blockers (44%) and loop diuretics (22.3%). Only 4.1% of the patients have experienced barriers to follow medication schedule. Half of the sample reported experiencing excellent or good self rated health, while the other half reported average or poor self rated health. Half of the participants had an incision and 14% had a wound (of any type). Most of the incisions were either on the abdomen (19%) or upper body (18.7). Only about 4% of patients experienced impaired orientation or altered levels of consciousness. Small percentage of patients had nutrition issues (6.4%) or were identified at a risk for eating poorly (8.5%). About half of the patients were hospitalized either one time (27.4%) or two or more times (21%) during the past 6 months. Similar percentages experienced emergency department visit during the past 6 months.

As expected from a sample of home health patients, most of the cases summaries presented at least one type of functional limitation. Half of the sample had ambulation limitations (use of assistive equipment, assistive person or both), 40% used equipment or needed help with transfers and third of the patients required equipment or help with toileting, bathing and dressing. In addition, many patients had decline in functional status during the hospitalization. For instance, 37% experienced decline in ambulation status and third had decline in transfers. In terms of the psychosocial and individual characteristics, fifth of the patients had an impaired ability to learn and 5.8% reported having a financial concern. About 12% presented with depression symptoms of lack of pleasure or feeling hopeless during the past two weeks. A fifth of the sample had mental health issues or reported pain at rest.

Most of the case summaries related to patients living in houses (79.2%) rather than apartments etc. Majority of the participants required some kind of equipment (e.g. cane or walker) upon their discharge and 36% expressed home accessibility concerns. Almost 70% patients of the caregivers were children or spouses who were living with the patient and third of the patients were living alone. Overall, 80% of the patients had a caregiver and most of the caregivers (70.6%) were able to help. Most of the caregivers

(71.7%) were available to help on weekdays and weekends and 38% were available 24/7. Eight percent of the caregivers were indicated as having inadequate understating of patient's condition.

Table 10: Full training sample demographics and clinical characteristics by patient's priority. The variable importance index is a fraction of the unique variable responses selected by the experts out of all available choices for this variable.

Variable name	**Low/ Medium priority (n=178)**	**% Low/ Medium priority**	**High priority (n=165)**	**% High priority**	**Overall Training sample (n=343)**	**% overall**	**p-value**	**% selected by experts - variable importan ce index**
Age at admission	69.2	9	70.2	10.1	69.7	9.5	0.35	41.4
Race							0.08	2.9
White	110	61.8	109	66.1	219	63.8		0.9
Black or Afro American	52	29.2	51	30.9	103	30		2.9
Other	16	8.99	5	3	21	6.1		23.8
Gender (male)	96	53.9	79	47.9	175	51	0.26	5.2
Marital status (Married)	93	52.3	83	50.3	176	51.3	0.2	19.2
Employment status							0.591	16.3
Employed	38	22.2	30	18.8	68	19.8		17.6
Not-employed	103	60.2	105	65.6	208	60.6		8.7
Disabled	30	17.6	25	15.6	55	16		47.3
Education							0.747	14.9
High school or less	105	60.7	98	62.4	203	59.2		15.8
College or more	68	39.3	59	37.6	127	37		15
Hospital summary								
Number of comorbid conditions	10.8	5.1	12.3	6.9	11.5	5.6	**0.001**	43.1
Length of hospital stay	5	3.5	5.9	4	5.5	3.8	**0.016**	29.7
Number of medications	10.8	5.4	11.9	4.5	11.4	5	**0.035**	54.5
Admission type							0.674	39.9

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Elective	73	41	64	38.8	137	39.9		34.3
Emergency	105	59	101	61.2	206	60.1		43.7
Primary diagnosis heart diseases (level 2)	30	17	23	14.4	53	15.5	0.456	56.6
Primary diagnosis urinary conditions (level 2)	8	4.5	8	5	16	4.7	0.877	56.3
Primary diagnosis complications (level 2)	11	6.3	12	7.5	23	6.7	0.686	69.6
Comorbid condition: hypertension (level 3)	83	51.2	79	48.8	162	47.2	0.817	14.2
Comorbid condition: coronary artery disease (level 3)	61	53.5	53	46.5	114	33.2	0.673	18.4
Comorbid condition: dysrhythmias (level 3)	55	50.9	53	49.1	108	31.5	0.808	32.4
Comorbid condition: aftercare (e.g. long use of anticoagulants, level 3)	56	57.1	42	42.9	98	28.6	0.219	22.4
Comorbid condition: heart failure (level 3)	43	49.4	44	50.6	87	25.4	0.594	51.7
Comorbid condition: kidney failure (level 3)	41	47.7	45	52.3	86	25.1	0.365	40.7
Comorbid condition: hypertension with complications (level 3)	39	50.6	38	49.4	77	22.4	0.804	24.7
Comorbid condition: anemia (level 3)	37	48.7	39	51.3	76	22.2	0.525	17.1
Comorbid condition: acute renal failure (level 3)	25	42.4	34	57.6	59	17.2	0.108	47.5

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Comorbid condition: complications (level 3)	27	45.8	32	54.2	59	17.2	0.3	35.6
Comorbid condition: COPD (level 3)	23	57.5	17	42.5	40	11.7	0.45	35
Comorbid condition: obesity (level 3)	19	51.4	18	48.6	37	10.8	0.944	21.6
Comorbid condition: depression (level 3)	13	39.4	20	60.6	33	9.6	0.131	48.5
Comorbid condition: pulmonary HF (level 3)	12	40	18	60	30	8.7	0.172	33.3
Comorbid condition: nervous system (level 3)	13	44.8	16	55.2	29	8.5	0.426	34.5
Comorbid condition: liver diseases (level 3)	9	45	11	55	20	5.8	0.525	55
Comorbid condition: metabolic conditions (level 3)	7	43.8	9	56.3	16	4.7	0.504	50
Comorbid condition: ulcer decubitus (level 3)			6	100	6	1.7	**0.01**	66.7
Minor therapeutic procedure	80	48.8	84	51.2	164	47.8	0.269	42.7
Major therapeutic procedure	82	51.3	78	48.8	160	46.6	0.823	60
Personal/family history of mental conditions	37	52.9	33	47.1	70	20.4	0.857	24.3
Personal/family history of neoplasms	45	57.7	33	42.3	78	22.7	0.244	19.2
Personal/family history of circulatory diseases	21	43.8	27	56.3	48	14	0.223	45.8
Drug class: Anticoagulants	96	51.1	92	48.9	188	54.8	0.734	21.3

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Drug class: Opioids	93	51.7	87	48.3	180	52.5	0.929	27.2
Drug class: NSAIDs	82	49.7	83	50.3	165	48.1	0.433	7.3
Drug class: Beta blockers	78	52.7	70	47.3	148	43.1	0.749	8.8
Drug class: Loop diuretics	31	41.3	44	58.7	75	21.9	**0.038**	28
Drug class: Insulin	30	55.6	24	44.4	54	15.7	0.588	18.5
Drug class: Benzodiazepines	24	58.5	17	41.5	41	12	0.364	14.6
Some/major barriers to follow med schedule	5	35.7	9	64.3	14	4.1	0.202	100
Health Characteristics								
Self-rated health							**0.012**	12
Excellent/ good	104	58.4	74	41.6	178	51.9		9.6
Average/ poor	71	44.7	88	55.3	159	46.4		15.1
Vision minor/ major issues	59	51.8	55	48.2	114	33.2	0.944	24.6
Hearing some/ major issues	18	40.9	26	59.1	44	12.8	0.132	36.4
Wound presence	16	33.3	32	66.7	48	14	**0.005**	66.7
Incision presence	88	51.8	82	48.2	170	49.6	0.962	64.1
Incision location							0.924	65.9
Abdomen	32	49.2	33	50.8	65	19		56.9
Upper body	33	51.6	31	48.4	64	18.7		67.2
Lower body	23	56.1	18	43.9	41	12		78
Conscious level: some/major issues	5	35.7	9	64.3	14	4.1	0.232	85.7
Orientation: some/ major issues	5	33.3	10	66.7	15	4.4	0.156	100

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Fall risk: at risk	73	59.3	50	40.7	123	35.9	0.039	90.2
Braden score: at risk	14	38.9	22	61.1	36	10.5	0.099	47.2
Nutrition or weight loss issues	10	45.5	12	54.5	22	6.4	0.521	45.5
Risk for eating poorly	14	48.3	15	51.7	29	8.5	0.67	44.8
Past 6 months hospital stay							0.135	21.9
Not at all	94	55.3	76	44.7	170	49.6		
One time	51	54.3	43	45.7	94	27.4		28.7
Two or more times	30	41.7	42	58.3	72	21		66.7
Past 6 months ED visit		0					0.531	22.7
Not at all	99	54.7	82	45.3	181	52.8		0
One time	44	50.6	43	49.4	87	25.4		37.9
Two or more times	31	47	35	53	66	19.2		68.2
Functional status								
Ambulation: assistive equipment/ person	82	47.4	91	52.6	173	50.4	**0.049**	48.6
Transfers: assistive equipment/ person	58	43.6	75	56.4	133	38.8	**0.01**	46.6
Toileting: assistive equipment/ person	47	41.6	66	58.4	113	32.9	**0.004**	48.7
Bathing: assistive equipment/ person	51	45.1	62	54.9	113	32.9	0.07	47.8
Dressing: assistive equipment/ person	44	41.9	61	58.1	105	30.6	**0.012**	41
Eating: assistive equipment/ person	10	33.3	20	66.7	30	8.7	**0.035**	33.3

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Communication: some/ major difficulty	3	30	7	70	10	2.9	0.159	40
Ambulation change							0.234	33
Improvement	17	42.5	23	57.5	40	11.7		37.5
Decline	65	51.2	62	48.8	127	37		64.6
No change	91	56.9	69	43.1	160	46.6		6.9
Transfers change							**0.039**	28.4
Improvement	11	35.5	20	64.5	31	9		41.9
Decline	48	48	52	52	100	29.2		71
No change	113	57.7	83	42.3	196	57.1		4.6
Toileting change							**0.025**	24
Improvement	13	35.1	24	64.9	37	10.8		32.4
Decline	44	48.9	46	51.1	90	26.2		64.4
No change	115	58.1	83	41.9	198	57.7		4
Bathing change							**0.047**	25.2
Improvement	14	36.8	24	63.2	38	11.1		34.2
Decline	44	48.4	47	51.6	91	26.5		61.5
No change	110	57.3	82	42.7	192	56		6.3
Dressing change							0.06	20.9
Improvement	12	40	18	60	30	8.7		33.3
Decline	36	44.4	45	55.6	81	23.6		58
No change	119	56.9	90	43.1	209	60.9		4.8
Eating change							0.288	9.1

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Improvement	7	63.6	4	36.4	11	3.2		45.5
Decline	10	38.5	16	61.5	26	7.6		50
No change	148	52.3	135	47.7	283	82.5		3.9
Communication change							0.624	3.9
Improvement	3	42.9	4	57.1	7	2		42.9
Decline	3	37.5	5	62.5	8	2.3		25
No change	167	52.5	151	47.5	318	92.7		2.5
Individual and Psychosocial Characteristics								
Reported pain at rest	42	58.3	30	41.7	72	21	0.222	33.3
Ability to learn: some or major limitations	24	40.7	35	59.3	59	17.2	**0.051**	71.2
Financial concern present	10	50	10	50	20	5.8	0.845	70
Depression: feeling no pleasure	17	43.6	22	56.4	39	11.4	0.293	66.7
Depression: feeling hopeless	17	42.5	23	57.5	40	11.7	0.225	50
Mental health issues	30	44.8	37	55.2	67	19.5	0.215	58.2
Living Environment								
Living arrangement							**0.042**	14.6
House	151	55.1	123	44.9	274	79.9		11.7
Apt and other	23	40.4	34	59.6	57	16.6		31.6
Lives with		0				0	0.573	46.3

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
With family or other	123	51.3	117	48.8	240	70		32.1
Lives alone	53	54.6	44	45.4	97	28.3		81.4
Home accessibility concerns	68	55.3	55	44.7	123	35.9	0.399	70.7
Equipment use at discharge	93	46	109	54	202	58.9	**0.009**	60.4
Caregiver characteristics								
Caregiver present	149	52.1	137	47.9	286	83.4	0.792	40.2
Caregiver relationship							0.171	24.8
Spouse/children	114	49.6	116	50.4	230	67.1		18.3
Others	29	60.4	19	39.6	48	14		56.3
Caregiver able to help	106	52.5	96	47.5	202	70.6	0.995	51.5
Caregiver availability days							0.944	27.2
Weekdays & weekends	102	49.8	103	50.2	205	71.7		5.4
Weekdays	8	44.4	10	55.6	18	6.3		38.9
Weekends	4	57.1	3	42.9	7	2.4		57.1
Information missing/or non available	29	50.9	28	49.1	57	19.9		91.2
Caregiver availability times							0.946	42.2
24/7	56	51.4	53	48.6	109	38.1		23.9
daytime+eve/daytime+night	18	47.4	20	52.6	38	13.3		10.5
daytimeOReveORnight	18	54.5	15	45.5	33	11.5		48.5

Variable name	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value	% selected by experts - variable importance index
Information missing/or non available	29	50.9	28	49.1	57	19.9		94.7
Caregiver willingness to help							0.824	37.1
Willing to help	107	52.5	97	47.5	204	71.3		14.7
Information missing/or non available	42	51.2	40	48.8	82	28.7		92.7
Caregiver understanding of patient condition							0.95	24.1
Adequate understanding	96	52.7	86	47.3	182	63.6		12.1
Inadequate understand	12	54.5	10	45.5	22	7.7		63.6
Information missing/or non available	29	50.9	28	49.1	57	19.9		47.4

When reviewing the case summaries, experts helped us to achieve two main goals: (1) understand the patient's priority for the first home health nursing visit (by selecting priority category on the sliding scale) and (2) identify clinical factors that affected their decisions (by selecting the individual/multiple clinical characteristics presented on the study website). Results of the experts' choices are presented in Table 11. There are two central considerations when examining experts' responses: first, it is important to see what variables differ significantly between low/medium and high priority cases. Second, it is important to understand how many instances of the individual values of a specific variable were selected. For example: variable indicating issues with toileting (assistive person/equipment needed) differed significantly between the priority levels (p=.02) and was selected 55 times (48.7% out of total present). Significant p-value and frequent selection by the experts suggest the relative importance of this variable. Information on the relative importance (fraction of the category selected by the experts out of total number of times it appears in case summaries) is presented in Table 10, last column.

Based on the combination of frequency and statistical significance ($p<.1$) of experts responses, the most important socio-demographic characteristics were: age (selected 41% of the times, low/medium group average 70.9- high priority group average 76.4, p=.001); employment status, especially if the person was disabled (selected 47.3% of the times, p=.023); and education (selected in 15% of the cases with 65.6% patients with high school or less education assigned a high priority, p=.008). In terms of clinical characteristics, the following variables were indicated as important: number of comorbid conditions (selected 43.1% of the times, low/medium group average 12.6- high priority group average 14.4, p=.05), comorbid conditions of hypertension (69.6% of patients with this condition were in the high priority group, p=.033), congestive heart failure (65.7% of patients with this condition were in the high risk priority, p=.008), kidney failure (69.6% of patients with this condition were in the high priority group, p=.028), hypertension with complications (73.7% of patients with this condition were in the high priority group, p=.022), acute renal failure (75% of patients with this condition were in the high priority group, p=.003), depression (68.8% of patients with this condition were in the high priority group, p=.061); and minor therapeutic procedures (68.6% of patients with this procedure were in the high risk group, p=.022). Also, patients with personal or family history of neoplasms (p=.016) and mental health issues (p=.002) were frequently indicated as high priority. Of the drug classes, only beta-blockers achieved moderate significance in the expert responses (p=.066), although most of the patients (76.9%) taking those medications were assigned low/medium priority. Experts also indicated that the presence of wounds (78.1% of patients with a condition were in the high priority group, p=.052) is an important factor associated with decisions on first home health nursing visit priority.

Most of the functional status variables were considered important when deciding on patients' priority. Issues related to ambulation (p=.012), transfers (p=.039), toileting (p=.02), and bathing (p=.092) were all associated with decisions on assigning high priority. Those variables were also frequently selected, on average in 45% of the cases. In addition, current functional status variables were often selected by experts in conjunction with functional status change variables, especially decline. However, no functional status change variables were significantly different between the low/medium and high priority patients independently. Variables related to home environment and caregiver characteristics, although were relatively frequently selected by the experts, did not differ significantly between the samples.

Experts' helped us to identify some of the significant variables by explicitly indicating them in the case summaries. It was also informative to examine the differences between the expert response and distribution of the variables between low/medium and high priority categories in the training sample using all patient data (Table 11). This paragraph reviews additional significant variables identified in the overall training sample. In terms of the clinical characteristics, I found that a loop diuretic was usually taken by patients in the high priority group (58.7% of patients with the medication were in the high priority group, p=.038) and slightly more patients with average or poor self-rated health were in the high priory group (55.3%, p=.012). Fall risk differed significantly between the samples, although more patients at risk (59.3%, p=.039) were present in low/medium priority categories. Additional current functional status variables (dressing and eating) and most of the change in functional status variables were significantly different, with more patients experiencing issues or status decline assigned to high priority category. Finally, ability to learn (59.3% of patients with limited ability to learn were in the high priority group, p=.051) and living arrangement (59.6% of the patients living in the apartment or other place rather than house were in the high priority group, p=.042) also emerged as significant.

Table 11: Experts response frequencies and bivariate comparisons by patient's priority

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Age at admission	142	70.9	9.1	76.4	9.8	73.8	9.8	**0.001**
Race	10							0.329
White	2	2	100			2	20	
Black or AA	3	2	66.7	1	33.3	3	50	
Other	5	2	40	3	60	5	30	
Gender (male)	18	7	38.9	5	61.1	12	66.7	0.732
Marital status (Married)	66	15	22.7	6	77.3	21	31.8	**0.001**
Employment status	56							0.023
Employed	12	10	83.3	2	16.7	12	21.4	
Not-employed	18	5	27.8	13	72.2	18	32.2	
Disabled	26	11	42.3	15	57.7	26	46.4	
Education	51							**0.008**
High school or less	32	11	34.4	21	65.6	32	62.7	
College or more	19	18	94.7	1	5.3	19	37.3	
Hospital summary								
Number of comorbid conditions	148	12.6	5.2	14.4	5.5	13.7	5.5	**0.05**
Length of hospital stay	102	6.4	4.5	8.6	3.8	7.6	4.2	**0.009**
Number of medications	187	12.3	4.9	13.4	4	12.9	4.4	**0.05**
Admission type	137							0.389
Elective	47	24	38.1	23	31.1	47	34.3	
Emergency	90	39	61.9	51	68.9	90	65.7	

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Primary diagnosis heart diseases (level 2)	30	17	20.5	13	12.1	30	4.8	0.298
Primary diagnosis urinary conditions (level 2)	9	5	6	4	3.7	9	1.4	0.584
Primary diagnosis complications (level 2)	16	7	8.4	9	8.4	16	2.6	0.504
Comorbid condition: hypertension (level 3)	23	7	30.4	16	69.6	23	3.7	**0.033**
Comorbid condition: coronary artery disease (level 3)	21	11	52.4	10	47.6	21	3.3	0.963
Comorbid condition: dysrhythmias (level 3)	35	14	40	21	60	35	5.6	0.137
Comorbid condition: aftercare (e.g. long use of anticoagulants, level 3)	22	11	50	11	50	22	3.5	0.854
Comorbid condition: heart failure (level 3)	45	15	33.3	30	66.7	45	7.2	**0.008**
Comorbid condition: kidney failure (level 3)	35	12	34.3	23	65.7	35	5.6	**0.028**
Comorbid condition: hypertension with complications (level 3)	19	5	26.3	14	73.7	19	3	**0.022**
Comorbid condition: anemia (level 3)	13	4	30.8	9	69.2	13	2.1	0.12
Comorbid condition: acute renal failure (level 3)	28	7	25	21	75	28	4.5	0.003
Comorbid condition: complications (level 3)	21	7	33.3	14	66.7	21	3.3	0.079
Comorbid condition: COPD	14	5	35.7	9	64.3	14	2.2	0.216

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
(level 3)								
Comorbid condition: obesity (level 3)	8	1	12.5	7	87.5	8	1.3	**0.024**
Comorbid condition: depression (level 3)	16	5	31.3	11	68.8	16	2.6	0.061
Comorbid condition: pulmonary HF (level 3)	10	3	30	7	70	10	1.6	0.16
Comorbid condition: nervous system (level 3)	10	5	50	5	50	10	1.6	0.903
Comorbid condition: liver diseases (level 3)	11	4	36.4	7	63.6	11	1.8	0.2
Comorbid condition: metabolic conditions (level 3)	8	2	25	6	75	8	1.3	0.123
Comorbid condition: ulcer decubitus (level 3)	4			4	100	4	0.6	0.037
Minor therapeutic procedure	70	22	31.4	48	68.6	70	23.2	**0.001**
Major therapeutic procedure	96	45	46.9	51	53.1	96	31.8	0.246
Personal/family history of mental conditions	17	4	23.5	13	76.5	17	21	**0.016**
Personal/family history of neoplasms	15	2	13.3	13	86.7	15	18.5	**0.002**
Personal/family history of circulatory diseases	22	8	36.4	14	63.6	22	27.2	0.132
Drug class: Anticoagulants	40	18	45	22	55	40	8	0.353
Drug class: Opioids	49	26	53.1	23	46.9	49	9.7	0.86
Drug class: NSAIDs	12	4	33.3	8	66.7	12	2.4	0.19
Drug class: Beta blockers	13	10	76.9	3	23.1	13	2.6	0.066

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Drug class: Loop diuretics	21	8	38.1	13	61.9	21	4.2	0.191
Drug class: Insulin	10	5	50	6	50	10	2	0.664
Drug class: Benzodiazepines	6	3	50	3	50	6	1.2	0.925
Some/major barriers to follow med schedule	14	1	7.1	13	92.9	14	100	0.531
Health Characteristics								
Self-rated health	41							0.365
Excellent/good	17	11	64.7	6	35.3	17	41.5	
Average/poor	24	8	33.3	16	66.7	24	58.5	
Vision minor/major issues	28	12	42.9	16	57.1	28	24.6	0.551
Hearing some/major issues	16	4	25	12	75	16	36.4	0.849
Wound presence	32	7	21.9	25	78.1	32	66.7	**0.052**
Incision presence	109	55	50.5	54	49.5	109	64.1	0.9
Incision location	112							0.822
Abdomen	37	17	45.9	20	54.1	37	33	
Upper body	43	22	51.2	21	48.8	43	38.4	
Lower body	32	17	53.1	15	46.9	32	28.6	
Conscious level: some/major issues	10	4	40	6	60	10	71.4	0.1
Orientation: some/major issues	13	4	30.8	9	69.2	13	86.7	0.143
Fall risk: at risk	111	63	56.8	48	43.2	111	90.2	0.762
Braden score: at risk	17	4	23.5	13	76.5	17	47.2	0.52
Nutrition or weight loss issues	10	4	40	6	60	10	45.5	0.188
Risk for eating poorly	13	3	23.1	10	76.9	13	44.8	**0.046**

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Past 6 months hospital stay	75							0.389
Not at all								
One time	27	12	44.4	15	55.6	27	35.5	
Two or more times	48	16	33.3	32	66.7	48	64.5	
Past 6 months ED visit	78							0.97
Not at all								
One time	33	12	36.4	21	63.6	33	41.3	
Two or more times	45	16	35.6	29	64.4	45	58.7	
Functional status								
Ambulation: assistive equipment/person	84	32	38.1	52	61.9	84	70.5	**0.012**
Transfers: assistive equipment/person	62	20	32.3	42	67.7	62	65.2	0.039
Toileting: assistive equipment/person	55	20	36.4	35	63.6	55	61.7	**0.02**
Bathing: assistive equipment/person	54	20	37	34	63	54	57.4	0.092
Dressing: assistive equipment/person	43	13	30.2	30	69.8	43	58.1	0.27
Eating: assistive equipment/person	10	3	30	7	70	10	22.7	0.208
Communication: some/major difficulty	4			4	100	4	19.1	0.178
Ambulation change	108							0.845
Improvement	15	7	46.7	8	53.3	15	13.9	
Decline	82	37	45.1	45	54.9	82	75.9	

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
No change	11	4	36.4	7	63.6	11	10.2	
Transfers change	93							0.61
Improvement	13	4	30.8	9	69.2	13	14	
Decline	71	31	43.7	40	56.3	71	76.3	
No change	9	3	33.3	6	66.7	9	9.7	
Toileting change	78							0.446
Improvement	12	6	50	6	50	12	15.4	
Decline	58	28	48.3	30	51.7	58	74.4	
No change	8	2	25	6	75	8	10.3	
Bathing change	81							0.703
Improvement	13	6	46.2	7	53.8	13	16.1	
Decline	56	26	46.4	30	53.6	56	69.1	
No change	12	4	33.3	8	66.7	12	14.8	
Dressing change	67							0.763
Improvement	10	4	40	6	60	10	14.9	
Decline	47	20	42.6	27	57.4	47	70.2	
No change	10	3	30	7	70	10	14.9	
Eating change	29							0.199
Improvement	5	2	40	3	60	5	17.2	
Decline	13	7	53.8	6	46.2	13	44.8	
No change	11	2	18.2	9	81.8	11	37.9	
Communication change	13				100			0.164
Improvement	3			3	100	3	23.1	

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Decline	2			2	100	2	15.4	
No change	8	4	50	4	50	8	61.5	
Individual and Psychosocial Characteristics								
Reported pain at rest	24	13	54.2	11	45.8	24	82.7	0.812
Ability to learn: some or major limitations	42	13	31	29	69	42	80.7	0.082
Financial concern present	14	6	42.9	8	57.1	14	53.8	0.088
Depression: feeling no pleasure	26	12	46.2	14	53.8	26	86.7	0.219
Depression: feeling hopeless	20	14	70	16	30	20	58.9	0.298
Mental health issues	39	14	35.9	25	64.1	39	88.6	0.318
Living Environment								
Living arrangement	50							0.9
House	32	16	50	16	50	32	64	
Apt and other	18	5	27.8	13	72.2	18	36	
Lives with	156							0.558
With family or other	77	40	51.9	37	48.1	77	49.3	
Lives alone	79	42	53.2	37	46.8	79	50.7	
Home accessibility concerns	87	35	40.2	42	59.8	77	88.6	0.565
Equipment use at discharge	122	45	36.9	69	63.1	114	93.4	**0.05**
Caregiver charachteristics								
Caregiver present	115	41	35.7	22	64.3	63	54.8	0.184
Caregiver relationship	69							0.505
Spouse/children	42	24	57.1	18	42.9	42	60.8	

Variable name	Number of times selcted by experts (N of clicks)	Low/ Medium priority (n=178)	% Low/ Medium priority	High priority (n=165)	% High priority	Overall Training sample (n=343)	% overall	p-value
Others	27	16	59.3	11	40.7	27	39.2	
Caregiver able to help	104	14	13.5	9	86.5	23	22.1	0.261
Caregiver availability days	78							0.346
Weekdays & weekends	11	8	72.7	3	27.3	11	14.9	
Weekdays	7	3	42.9	4	57.1	7	9.5	
Weekends	4	3	75	1	25	4	5.4	
Information missing/or non available	52	21	40.4	31	59.6	52	70.3	
Caregiver availability times	100							0.469
24/7	26	15	57.7	11	42.3	26	26	
daytime+eve/daytime+night	4	2	50	2	50	4	4	
daytimeORreveORnight	16	9	56.3	7	43.8	16	16	
Information missing/or non available	54	28	51.9	26	48.1	54	54	
Caregiver willingness to help	106							0.161
Willing to help	30	20	66.7	10	33.3	30	28.3	
Information missing/or non available	76	31	40.8	45	59.2	76	71.7	
Caregiver understanding of patient condition	63							0.53
Adequate understanding	22	13	59.1	9	40.9	22	34.9	
Inadequate understand	14	6	42.9	8	57.1	14	22.2	
Information missing/or non available	27	11	40.7	16	59.3	27	42.9	

In summary, nine variables appeared significantly different between the low/medium and high risk samples in both experts' responses and full training sample data were (parenthesis present values from the full training sample): number of comorbid conditions (10.8 vs. 12.3 comorbid conditions on average, p=.001), length of stay (5 vs. 5.9 days on average, p=.016), number of medications (10.8 vs. 11.9 medications on average, p=.035); comorbid condition of ulcer decubitus (all 6 cases were in the high priority category, p=037); wound presence (66.7% in high priority category, p=.005); ambulation limitation- assistive equipment/person (52.6% in high priority category, p=.049); transfers limitations- assistive equipment/person (56.4% in high priority category, p=.01); toileting limitations- assistive equipment/person (58.4% in high priority category, p=.004); and equipment use at discharge (54% in high priority category, p=.009).

Finally, I also conducted bivariate comparisons to compare the training and testing samples. No significant differences were identified between the randomly split samples.

b. Selecting the most informative variable subset for the final model

To confirm the applicability of the variable categorizations (conducted in Step 1) and validate the results of the bivariate comparisons (conducted in Step 2.a), two statistical techniques were applied. First, I applied data mining and used three previously described methods for feature selection (Information Gain, Gain Ration and Chi-square evaluator) to identify variables with the highest information potential when estimating the outcome. Table 12 presents the 20 highest ranked variables (in terms of the contribution to predicting the outcome variable) from each of the approaches and summarizes an average ranking by individual variable. 10 fold validation was used to validate the choice of the variables. An additional method that pays more attention to interactions between the variables, the Correlation Feature Selection (CFS), was also applied using different search algorithms (Witten et al., 2011). No new variables were identified when using this method.

Table 12: Average ranking of the individual variables in terms of association with the outcome based on the feature selection using data mining

Rank	Varible name	Information Gain Ranking Filter: Ranker	Gain Ratio feature evaluator: Ranker	Chi-squared Ranking Filter	Average of rankings
1	Number of comorbid conditions	1	4	1	2
2	Toileting current (dichotomous)	2	6	2	3.3
3	Transfer current (dichotomous)	3	7	3	4.3
4	Wound presence	5	3	5	4.3
5	Number of discharge medications	6	2	6	4.7
6	Toileting changed	4	9	4	5.7
7	Bathing current (dichotomous)	7	8	7	7.3
8	Comrobid class: ulcer decubitus	10	1	11	7.3
9	Dressing current	8	12	8	9.3

Rank	Varible name	Information Gain Ranking Filter: Ranker	Gain Ratio feature evaluator: Ranker	Chi-squared Ranking Filter	Average of rankings
	(dichotomous)				
10	Ambulation current (dichotomous)	9	13	9	10.3
11	Self rated health	11	16	10	12.3
12	Drug class: loop diuretics	13	15	13	13.7
13	Fall risk	12	18	12	14
14	Braden score	16	11	16	14.3
15	Comrobid class: kidney failure	14	17	14	15
16	Ambulation changed	15	20	15	16.7
17	Eating current (dichotomous)	18	14	18	16.7
18	Mental health issues	19	19	19	19
19	Past 6 month hospital stay	17	24	17	19.3
20	Equipment use	20	21	20	20.3

Secondly, I applied a bootstrap feature selection method in STATA. Using default settings of the procedure in STATA, 50 random samples were drawn from the full training dataset and the threshold for variable inclusion was set at p=.1. Summary count of the total number of times each variable was selected is presented in Table 13.

Overall, there was a good agreement (70%) between the methods in terms of the individual 20 variables selected as the most significant- 26 unique candidate variables were identified for use in final modeling.

Table 13: Bootstrap procedure results with 50 iterations. All the variables were intially included and then eliminated by backwards elimination method.

Rank	Bootstrap model selection (50 iterations)	Number of times each variable was selected
1	Number of discharge medications	42
2	Home accessibility	37
3	Equipment use	35
4	Number of comorbid conditions	33
5	Self-rated health	31
6	Vision problems	30
7	Primary diagnosis: heart diseases	27
8	Drug class: loop diuretics	27
9	Comrobid class: ulcer decubitus	25
10	Barriers following medications schedule	25
11	Living arrangement (dichotomous)	24
12	Depression: hopeless	24
13	Comrobid class: kidney failure	22
14	Wound presence	21
15	Toileting current (dichotomous)	20
16	Toileting changed	20
17	Dressing current (dichotomous)	20
18	Fall risk	19
19	Ambulation current (dichotomous)	17

Rank	Bootstrap model selection (50 iterations)	Number of times each variable was selected
20	Eating current (dichotomous)	16

c. Examining interactions between independent variables

Before conducting the final models, one more issue needed to be addressed, namely the interaction between the independent variables. If two explanatory variables are involved in a significant interaction, the effect of one variable might depend on the level of the other. To identify possible interactions, I conducted cross-tab analysis of all the variables (not presented). Several potential interactions were found and included in the final models, mostly in the function domain: (1) interaction between current ambulation status and change in ambulation status, (2) interaction between dressing and transfers statuses and (3) interaction between transfers and toileting statuses.

d. Qualitative validation based on experts' rationale descriptions

In one third of the case summaries, experts were asked to provide a brief description of the rationale for selecting the first visit priority. These rationale descriptions were usually brief, one/two sentence descriptions of the main factors that affected the expert's decision making in each case. One example is "Patient is high priority due to number of comorbidities that must be controlled, polypharmacy, multiple rehospitalizations/ER visits and wound care". I validated the factors identified by the data mining and other quantitative methods against experts' rationale descriptions. All the factors were addressed in the experts' responses.

STEP 3: Constructing and validating the best predictive model imitating experts' decisions on patient's priority (Aim 2).

a. Construction and validation of a predictive model

Only one variable (length of hospital stay) significantly different from bivariate comparisons (step 2.a) was not identified by the feature selection processes (step 2.b). This variable was added to the 26 unique variables. The 27 candidate variables and 3 interaction terms were put in the forward selection logistic model in STATA (Hosmer et al., 2013). Variables with $p<.15$ were retained in the model, which resulted in a subset of seven variables with no interaction terms. In the following iterations, the model's ROC was gradually improved by removing least significant variables ($p>.2$) and substituting variables with close meaning (for example, variable indicating self-reported depression was substituted by an indicator of a comorbid condition of depression, which slightly improved model's statistics) (Hosmer et al., 2013). All the testing of the model's predictive ability was performed on the testing holdout sample that consisted of a third of the cases from the original full dataset. Table 14 presents step-by-step iterations that were implemented to achieve the final model.

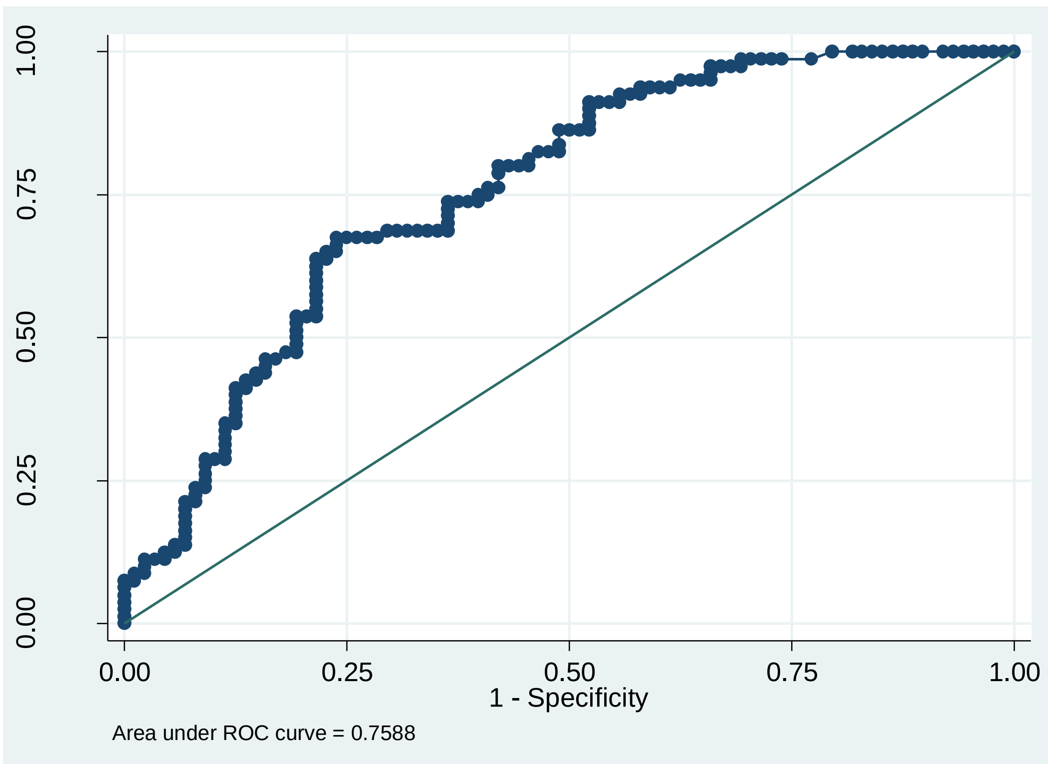
Table 14: Developing the final model step-by-step overview (V indicates variables included, X indicates variables excluded at each iteration).

Varible name	Iteration 1: stepwise selection	Iteration 2: removing the least signifcant	Iteration 3: removing the least signifcant	Iteration 4: removing the least signifcant	Iteration 5: replacing with simillar variables	Iteration 6: final model
Comrobid class: kidney failure	X	---	---	---	---	---
Comrobid class: ulcer decubitus	X	---	---	---	---	---
Drug class: loop diuretics	X	---	---	---	---	---
Equipment use	X	---	---	---	---	---
Ambulation changed	X	---	---	---	---	---
Ambulation current (dichotomous)	X	---	---	---	---	---
Bathing current (dichotomous)	X	---	---	---	---	---
Braden score	X	---	---	---	---	---
Eating current (dichotomous)	X	---	---	---	---	---
Fall risk	X	---	---	---	---	---
Interaction: current+change ambulation	X	---	---	---	---	---
Interaction: current dressing+current transfers	X	---	---	---	---	---
Interaction: current transfers and current toileting	X	---	---	---	---	---
Mental health	X	---	---	---	---	---
Past 6 month hospital stay	X	---	---	---	---	---
Self rated health	X	---	---	---	---	---

Varible name	Iteration 1: stepwise selection	Iteration 2: removing the least signifcant	Iteration 3: removing the least signifcant	Iteration 4: removing the least signifcant	Iteration 5: replacing with simillar variables	Iteration 6: final model
Toileting changed	X	---	---	---	---	---
Toileting current (dichotomous)	X	---	---	---	---	---
Transfer current (dichotomous)	X	---	---	---	---	---
Barriers following medications schedule	X	---	---	---	---	---
Home accessibility issues	X	---	---	---	---	---
Primary diagnosis: heart diseases	V	X	---	---	---	---
Vision issues	V	V	X	---	---	---
Living arrangement (dichotomous)	V	V	V	X	---	---
Dressing current (dichotomous)	V	V	V	V	X	---
Depression hopeless	V	V	V	V	V	X
Number of comorbid conditions	V	V	V	V	V	V
Wound presence	V	V	V	V	V	V
Number of discharge medications	V	V	V	V	V	V
Toileting current (dichotomous)	---	---	---	---	V	V
Comorbid condition: depression	---	---	---	---	---	V
ROC	69.9	71	71.6	72.3	74.9	75.9

Final model's ROC was 75.9%- see Figure 11 for the graphical representation of ROC. The receiver operating characteristic curves were used to determine the optimal cut-point for classification. The optimal (maximizing sensitivity while keeping specificity within reasonable limits) cut-point was 0.42. This corresponded to a sensitivity of 80% and specificity of 57.9%. In general, an AUC greater than 70% indicates an acceptable model for classifying participants with an outcome of interest against those without the outcome (Hosmer et al., 2013).

Figure 11: ROC curve final model



The final model included the following variables: number of comorbid conditions (OR 1.04, p=.11, CI: .99-1.08); number of discharge medications (OR 1.04, p=.08, CI: .87-1.09); presence of wounds (OR 1.88, p=.06, CI: .95-3.7); limitation in current toileting status (OR 2.02, p=.004, CI: .1.25-3.26); and presence of a comorbid condition of depression (OR 1.73, p=.15, CI: .8-3.6).

b. Model diagnostics

Several model diagnostics steps were performed to estimate and possibly improve the model's fit. Simply put, a model's fit is a numerical summary of the discrepancy between the observed values and the values expected under a statistical model. First, I examined the overall measures of fit for the final model. The value of Hosmer-Lemeshow goodness of fit statistic was 10.7 (p=.22) for the data in the training set model and 13.9 (p=.18) for the fitted model on the test sample. The lack of significance of the Hosmer-Lemeshow goodness of fit statistic indicate that the model fits the data well (Hosmer et al., 2013).

In addition, individual covariate patterns were examined to uncover patterns that do not fit or that have considerable influence on the estimated parameters (Hosmer et al., 2013). To identify those patterns, I performed graphical examination of the individual components of the summary statistics and examined other measures of the difference between the observed and fitted values (i.e. deviance, and influence). Plot of deviance (measure of difference between the observed and fitted values) suggests that neither of the covariate patterns have a distinctive poor fit- see Figure 12. Plot of influential covariate patterns identified one covariate pattern that was an outlier (point in the right upper corner of Figure 13). Only one observation had this covariate pattern (patient with a wound and relatively high number of medications and comorbid conditions was assigned a low/medium priority) and removing it did not improve the model's fit. The decision was made to leave this covariate in the model.

Figure 12: Plot of deviance versus the estimated probability from the fitted model.

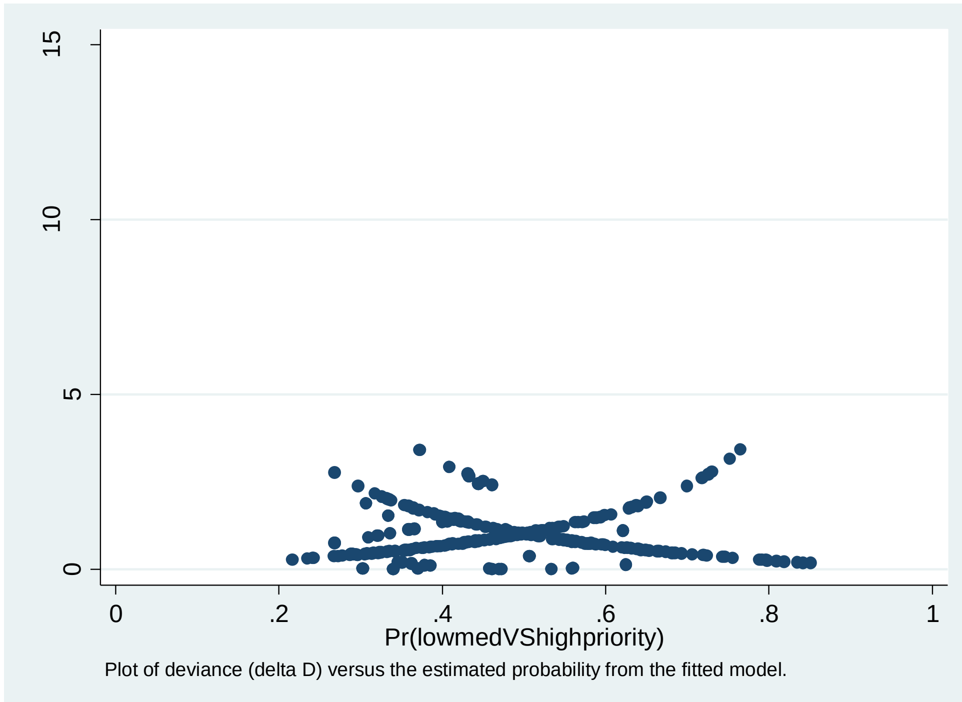
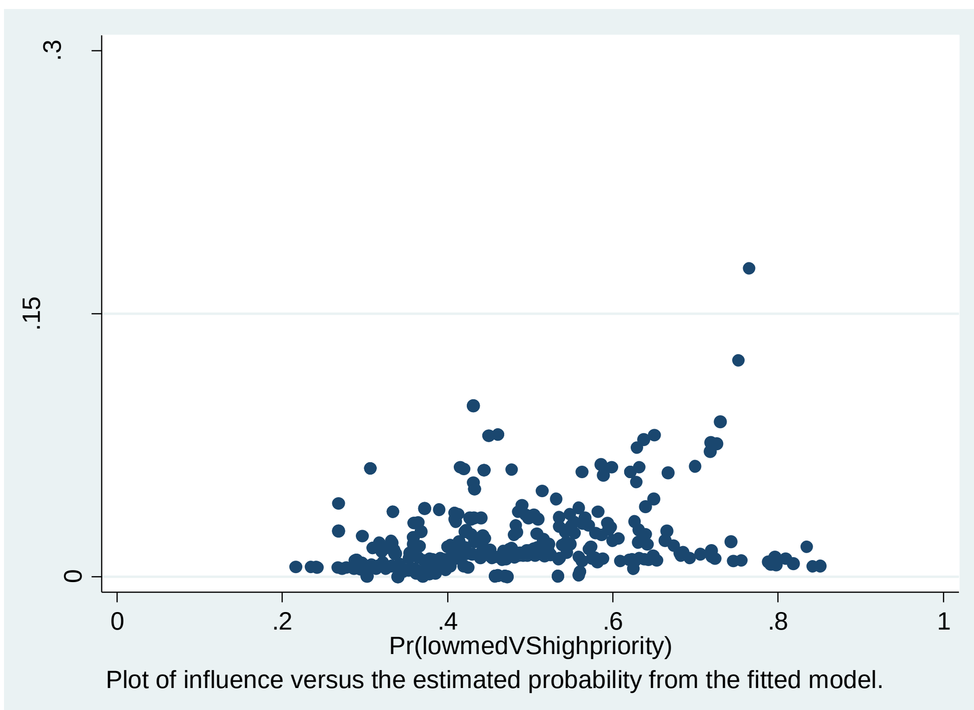


Figure 13: Plot of influence versus the estimated probability from the fitted model.



c. Experts' model validation

The final model was discussed with a convenience sample of three experts for validation. Experts were asked to assess the model's clinical relevance, applicability in practice and provide any other comment/suggestions. In general, all three experts approved the applicability of the model to their practice and clinical soundness of the five factors included. One specific question was about whether an ICD 9 code for depression should be used or the self-reported depression question (the two items had very similar statistical significance and resulted in the same model discriminative ability). According to the experts, using an often already existing information (ICD9) was preferable over creating a new self-reported depression question. Thus, the comorbid condition of depression (based on the ICD9 code) was used in the final model and the model was concluded as finalized.

Variables included in the final model were also validated against the rationale provided by experts. All the final variables frequently appeared in the experts' responses independently (e.g. a quote from expert's responses "need to assure pt is educated on medications and wound care") or as a part of certain variable subset, for example functional limitations were sometimes grouped together as in quote "patient has a higher priority for therapy based on surgical procedure and decline in functional status".

d. Other validation

Overall, 87 (16.8%) patients were rehospitalized to the same health system by 30 days and 124 (23.8%) patients were rehospitalized by 60 days in the full (n=519) study sample. High priority patients had 30% higher relative rates of 60 day rehospitalizations (crude difference 8%, 20% vs. 28% rehospitalized, p=.034) while at 30 days, the rehospitalization rates were 13% relatively higher, although not statistically significant (3.2% crude difference, 15.2% vs. 18.4% rehospitalized, p=.3). To address the possibility of bias associated with low priority patients, I took out the low priority group and re-ran the analysis. In the stepwise regression models, there was no difference in the factors selected for the final modeling. In the final model, the same variables remained significant with only small variation in coefficients (findings are not presented). Finally, I also compared the numbers of rehospitalized patients between this study and nationwide reports. The numbers of rehospitalized patients in this sample were comparable to the general rates of rehospitalizations among home health recipients discharged from hospitals (Anderson et al., 2005; Berry et al., 2011; Bowles, 2012; Markley, Sabharwal, Wang, Bigbee, & Whitmire, 2012b; C. Murtaugh, 2013).

Creating the tool

Finally, several adjustments were made to generate a clinical decision support tool that can be easily applicable in clinical practice, whether in computerized form or by hand. First, regression model beta coefficients were used to generate a specific score for each of the variables included in the final model. Long beta coefficients with up to seven numbers after decimal point (for example b=0.0376713 for each additional medication) were rounded-up to include less numbers after decimal. The logistic regression equation with beta coefficients was:

Priority Score (value > .42 indicated high priority) = regression intercept (-2.703) + number of comorbid conditions X .038 + number of discharge medications X .041 + presence of wounds X .601 + limitation in current toileting status X .702+ presence of a comorbid condition of depression X .598.

This regression equation was simplified until final version with rounded-up coefficients was developed. Using the logistic regression equation, I also made sure that optimal rounding of the coefficients was achieved while preserving the overall discriminative value of the model. Figure 14 presents the final version of the first home health visit prioritization tool with instructions on its possible application in practice.

Figure 14: PREVENT- Priority for First Home Health Visit Tool.

PREVENT

Rule: **Sum scores as follows. Any score >26 would suggest high priority for the first home health visit.**

Question: (Response =Score)	Score
Count the NUMBER OF MEDICATIONS prescribed to the patient =	
Count the NUMBER OF COMORBID CONDITIONS patient has =	
Does the patient have a comorbid condition of DEPRESSION (e.g. Depressive disorder, NEC)? **NO = 0** **YES = 15**	
Does the patient have WOUND of any type (e.g. pressure ulcer, vascular ulcer, etc.)? **NO = 0** **YES = 15**	
Does the patient have LIMITATION IN TOILETING functional ability requiring use of any assistive equipment, assistive person or both? **NO = 0** **YES = 20**	
Total Score:	
If total score is >26 then high priority for the first home health visit **If total score is =<26 then low or medium priority for the first home health visit**	

CHAPTER 5: DISCUSSION

Each year nursing administrators and intake nurses of more than 12,000 home health agencies across the US are deciding on and prioritizing health resource allocation for millions of older patients admitted to their agencies. Yet, there are no empirically derived standards to assist in making these important decisions. Patients discharged from hospitals are the most vulnerable population of home health patients. About a third of those patients are rehospitalized during the home health episode with up to 60% of the rehospitalizations occur within two weeks of hospital discharge. An increasing body of evidence shows that some patients should be prioritized for care close to hospital discharge (Fortinsky, Madigan, Sheehan, Tullai-McGuinness, & Kleppinger, 2014; O'Connor, Hanlon, & Bowles, 2014); however, there is no generalizable knowledge base to support those important decisions. This study was one of the first to examine factors affecting nurses' first home health visit prioritization decisions and develop a tool -further referred as "PREVENT" (PRiority home health Visit Tool)- to support patient prioritization decisions.

The general domains of factors identified in this study include comorbid conditions, medications, mobility status, depression and wound presence. In general, experts assigned about 10% of the case summaries to a low home health first nursing visit priority category, about 40% to a medium priority and the rest (about half of the sample) to a high priority category. The fact that only one-tenth of the cases were assigned low visit priority might suggest that this category has low relevance for patients discharged from hospitals to home health. Indeed, patients in this sample were relatively more medically complex than general recipients of home health services. For example, the average number of comorbid conditions among home health patients is 4.2 (Caffrey et al., 2011) while in this study it is significantly higher (11.5). Also, according to some reports, home health patients take an average of 9 medications daily (Triller, Clause, & Domarew, 2002) while patients in this study were prescribed 11.4 medications. An alternative explanation for relatively low numbers of patients in the low priority category might be the ambiguity of those decisions. According to the written rationale descriptions provided by the experts, case summaries presented fairly complex patients and it was often hard to decide with a high degree of certainty that a certain case might be considered as low risk. Those decisions might require additional contextual information as in the following example rationale provided by one of the experts:

> "This case looks like a low priority for first visit at first glance. She remains independent with ADLs, has a spouse who is willing and able to assist her, initial review of incision doesn't sound like it is infected. Medications look manageable. However, I made her the top of the low priority scale because she did have complications during surgery and a foreign body which may or may not still be in her body (not specified)."

It is evident that additional information on whether the foreign body was removed from the patient's body might have helped the expert's priority decision. To maintain sufficient statistical power for this analysis, I had to collapse low and medium priority categories. However, further investigation into the differences between low and medium priority patients is warranted, possibly including home health patients admitted from hospitals versus other settings.

Individual factors included in the PREVENT final tool are consistent with findings from an increasing body of literature on early rehospitalizations and hospitalization risk factors among community dwelling older adults recovering from an acute hospitalization episode. First, this study found that patients with higher number of comorbid conditions were assigned higher priority for the first home health nursing visit. This finding is in line with other home health studies indicating that patients with more than two (Rosati et al., 2003) or four (Rosati & Huang, 2007) secondary diagnoses have increased risk for rehospitalization. In a general sample of older patients outside of home health, those findings also hold true. For example, a recent study conducted on a nationwide sample of Medicare beneficiaries has shown that patients with five to nine chronic conditions had 2.5 higher odds and patients with ten or more conditions had six times higher odds of rehospitalization than patients with up to four conditions (Berkowitz & Anderson, 2013). Many other studies also supported the significant association between the number of comorbid conditions and negative outcomes (Bowles et al., 2009; Bowles et al., 2014; Fortinsky et al., 2014; O'Connor, 2012; Silverstein, Qin, Mercer, Fong, & Haydar, 2008).

One possible explanation for the strong association between the number of comorbid conditions and negative health outcomes was recently offered by Dickson and colleagues (2013). The researchers analyzed qualitative data and found that presence of multiple comorbid conditions might challenge patient's ability to engage in self-care by decreasing self-efficacy. On the other hand, home health patients discharged from hospitals might be present in an acute phase of major health transition and require a more targeted intervention focused on controlling one specific health concern. In further work, it might be interesting to explore whether early targeting of home health patients with high number of comorbid conditions for interventions increasing self-efficacy (i.e. coaching interventions that integrate self-care requirements and focus on developing skill in self-care across multiple chronic conditions) can improve outcomes compared to interventions focused on one specific condition, such as heart failure.

In this study, only one particular comorbid condition of depression was significantly associated with decisions on the priority for the first home health nursing visit. Indeed, having depression or depressive symptoms is a frequent risk factor in home health studies (Fortinsky et al., 2014; O'Connor, 2012). In general, it is well established that in the presence of depression, patients with other primary diagnoses experience higher rates of negative outcomes. For example, patients with heart failure and depression/depressive symptoms have up to two times higher odds of rehospitalizations (Rutledge, Reis, Linke, Greenberg, & Mills, 2006; Silver, 2010), up to two times higher odds of premature deaths (Fan et al., 2014; Rutledge et al., 2006; Silver, 2010) and an increased risk of poor functional status (Silver, 2010). Similar results were found in patients with depression and COPD (Atlantis, Fahey, Cochrane, & Smith, 2013), kidney failure (Farrokhi, Abedi, Beyene, Kurdyak, & Jassal, 2014) and acute coronary syndrome (Lichtman et al., 2014). Bowles and colleagues (2009) have also found that depressive symptoms serve as an important indicator of risk during care transitions.

One potential explanation for the negative effect of depression on diverse range of outcomes is high rates of medication non-adherence among patients with depression. For example, a meta-analysis of 31 studies examining the dynamic between depression and medication adherence in the context of chronic illnesses have found that patients with depression were two to three times more likely to be non-adherent compared to those who were not depressed (Grenard et al., 2011). Thus, if the tool developed in this study identifies patient with depression at a high priority for the first home health visit, more attention might be focused on interventions supporting medication adherence, such as a combination of educational, behavioral interventions and supportive technology (Haugh, 2014). Also, similar to the conclusions of the nationwide study of risk for rehospitalizations among home health recipients, initiatives aimed at actively treating depression might be considered early on in the home health episode (Fortinsky et al., 2014).

Experts in this study indicated that presence of a wound increases patient's priority for the first home health visit. This finding is congruent with most home health studies that identified that wounds increase patients' risk for rehospitalizations (Fortinsky et al., 2006; Fortinsky et al., 2014; O'Connor, 2012). Complications of wounds are also identified as one of the most common adverse events in home health setting (Masotti, McColl, & Green, 2010). Indeed, wounds are complex medical conditions that require early multi-faceted interventions, such as nutrition adjustments and high-tech treatment devices (Smith, 2012). A recent study that examined a nation-wide sample of 785 home health agencies showed that agencies that employed wound, ostomy, and continence (WOC) nurses had significantly better improvement outcomes for wounds than agencies without those specialists (Bliss, Westra, Savik, & Hou, 2014). One possible application for this study might be a suggestion to involve WOC nurses early on in home health episode for patients with wounds, if possible.

Number of discharge medications was yet another factor associated with higher priority for the first nursing visit. This finding is congruent with other studies in home health that found that numerous medications (e.g. more than five medications) and complex medication regimes are risk factors for rehospitalizations (O'Connor, 2012; Rosati et al., 2003; Rosati & Huang, 2007). In this study, an alarming feedback from experts identified numerous cases in which medications listed in discharged patients' summaries were confusing, conflicting or duplicative. For example, one expert indicated that one of the medications would have killed the patient if he followed the instructions exactly “Nitro [Nitroglycerin] q 5 minutes for 24 hours”. One of the clinical implications of this finding might be an increased attention to medication reconciliation early in the home health episode. Several medication complexity indexes are currently being tested and developed – e.g. an automated high risk medication regime algorithm in a home health care population (Olson et al., 2014)- and this study results highlight the critical need in application of those tools in practice.

In general, the use of high risk medications (e.g. antibiotics, glucocorticoids, narcotics, antiepileptic medications, antipsychotics, antidepressants) is often associated with poor outcomes among home health and other community dwelling older adults (Allaudeen et al., 2011; Budnitz et al., 2006; Budnitz et al., 2007; Budnitz et al., 2011). Interestingly, neither one particular medication group in this study have met the significance threshold to be included in the final model. One explanation might be the lack of statistical power since some of the medication groups were quite small. Alternatively, this finding might suggest an increasing awareness of medical professionals to the problems related to polypharmacy and complexities of medical regimes, rather than an individual medication. More detailed qualitative and quantitative examination of the medications issue is warranted.

In this study, limitations of functional status were identified as one of the most significant factors associated with priority for the first home health visit. This finding is consistent with other studies examining risk factors in home health (O’Connor, 2012; Rosati et al., 2003; Rosati & Huang, 2007). For example, Fortinsky and colleagues (2006) have found that increased functional disability levels were associated with higher hospitalizations among Medicare home health patients. Interestingly, although several measures of functional status were considered for the final models, only limitations in toileting met the significance threshold for the final PREVENT tool. On one hand, limitations in toileting provide a good summary of the patient's overall functional status: many patients with toileting issues would also have issues with ambulation, transfers etc. On the other hand, further investigation is warranted into whether limitation in toileting is the most important consideration for the first visit priority and further categorization beyond the dichotomous yes/no issues might be needed.

Notably, several factors identified in other studies were not significantly associated with home health nursing visit priority categorization in this study. For instance, patients' level of social support (O'Connor, 2012; Rosati et al., 2003) did not meet the threshold for statistical significance. Potentially, this was because most of the patients in this sample (more than two-thirds) had caregivers and, when present, caregivers were indicated as able and willing to help. Similarly, home physical environment or equipment used after discharge (Bowles et al, 2012; O'Connor, 2012) were not significantly correlated with priority decisions. It is possible that in this sample of urban patients with relatively well-established social support systems those factors were not very important. Further investigation with a more diverse patient sample is needed to validate the results of this study.

PREVENT's low/medium and high priority patients' categorization was validated against real life rehospitalization data in the sample. High priority patients had 30% higher rates of 60-day rehospitalizations (statistically significant, p=.034) and 13% higher rates of 30-day rehospitalizations (statistically not significant, p=.3). Those findings should be interpreted cautiously. On one hand, the fact that more high priority patients were rehospitalized indicates that the PREVENT tool was able to capture high risk patients. On the other hand, I do not know how soon those patients were seen by the nurses after the discharge and what interventions were provided to them in home health. I also don't know how many patients were rehospitalized outside of the original healthcare system (UPHS). Experimental study applying the PREVENT tool in practice is needed to investigate those issues in depth.

Today, much of the health policy discussion in the US is focusing on creating a shared view of post-acute care as a continuum of services rather than multiple sectors/ settings. For instance, a draft legislation titled "Improving Medicare Post-Acute Care Transformation Act of 2014" (IMPACT Act of 2014) takes a crucial step toward the modernization of Medicare payments to post-acute care providers and a more accountable, quality-driven benefit (Committee on Ways and Means, 2014). To advance those goals, several initiatives are aimed at creating a unified format for a continuity of care document. The continuity of care document might be defined as a core data set of the most relevant administrative, demographic, and clinical information facts about a patient's healthcare, covering one or more health care encounters (Office of National Coordinator for Health IT, 2014). Continuity of care document is currently one of the requirements under the CMS adopted Meaningful Use regulations that provide incentives for healthcare providers who use electronic health records (Office of National Coordinator for Health IT, 2014).

All the five elements presented in the final PREVENT tool of priority for the first home health visit are captured by the majority of existing continuity of care documents. For example, the CMS required (under the Meaningful Use regulations) continuity of care document is based on Health Level seven (HL7) standards that include necessary sections of medications, comorbid conditions, wounds and functional status (Health

Level Seven International, 2014). Similarly, a new standardized patient assessment tool developed with the support of CMS- the Continuity Assessment Record and Evaluation (CARE) Item Set that is currently being considered to replace various assessments conducted at the between-setting transitions in the US (Gage, 2014)- includes all the factors identified in this study. Items from CARE Item Set data or those captured by the HL7 continuity of care document format can be easily migrated to populate the PREVENT.

In terms of the operationalization of the PREVENT in practice, the tool can be used at various stages of the hospital-home health transition process. First, PREVENT can be implemented, automatically or by hand, at the point of hospital discharge. Then, first nursing visit recommendation can be sent electronically, by phone, fax or in any other form to the home health agency. The questions captured by PREVENT do not require any advanced clinical training, so the screening can be conducted by a diverse range of medical personnel starting from licensed practice nurses to attending physicians in the hospital. Another option is the application of the tool by the home health agency, for example the intake department personnel. The ideal application of the tool is its integration into the electronic health record of a hospital and automated transfer of priority information to the electronic systems of the home health agency. PREVENT’s easily computer-interpretable factors -that are already collected by many hospitals across the US in a form of continuity of care documents or routine medical records- make the integration of the tool into a relatively easy task. In addition, the tool would potentially yield better results if implemented together with other transition facilitating and enhancing tools such as the D2S2 (Bowles et al., 2009) or currently developed version of Bowles and colleagues' tool that aims to identify appropriate post acute care setting to which patients should be referred after discharge.

This study addresses several important healthcare policy initiatives. For example, the recent report of the Medicare Payment Advisory Commission (MedPac, 2014) suggested that significant health and financial gains can be achieved by targeting the population of home health patients, admitted from hospitals, for rehospitalization reduction programs. According to MedPac recommendations to the congress, the nationwide Hospital Readmissions Reduction Program (an initiative that incentives reduction and penalizes hospitals for 30-day rehospitalizations for certain medical conditions) should also become a requirement for home health settings. Based on the successful examples of transitional care models (e.g. Naylor and colleagues, 2004), MedPac specifically calls for more tools and interventions aimed at improving processes for hospital-home health transitions and better care coordination (MedPac, 2014). Results of this dissertation study offer one potential innovative tool to achieve those important goals.

Limitations

This study is not without limitations. First limitation pertains to the data presented to the experts in the case summaries. This study used cases of patients referred to home health settings in one particular healthcare system and, although this population of patients was similar to the nationwide sample in terms of rehospitalization numbers and major clinical factors (The National Association for Home Care & Hospice, 2010), patients' clinical characteristics or the decision process on who is referred to home health might vary. Future studies should possibly validate this study results in a larger and more geographically diverse patient sample.

Second potential limitation lies in the sample of recruited experts. Although several mechanisms were in place to ensure recruitment of appropriate study experts and effective training, experts' opinions on whom should be visited visit first were likely to vary. This variation in experts' opinions could have also contributed to the fact that I identified only a small percent (<10%) of case summaries in the low priority group. In this study, a decision was made to use an average nurses' response on individual case summaries rather than Delphi process in which a number of nurses would review the same case summary and agree on patient prioritization. Future studies can employ a more resource intensive validation approaches, similar to the Delphi methodology requiring experts' agreement on each particular decision, for example methodology implemented by Bowles and colleagues (2009). Another interesting and potentially less resource demanding innovative methodology to increase model's validity is to apply crowdsourcing, an approach in which large numbers of people collaborate by performing relatively simple tasks usually using applications distributed via the Internet (Good & Su, 2013). Several recent applications of crowdsourcing in medical domain – i.e. ontology validation and error checking (Mortensen, Musen, & Noy, 2013)- show promising results and might be potentially applied to the problem presented in this study.

Finally, because of the small numbers of observations in some of the categories of several categorical variables, I might have underestimated the effect of certain factors on visit priority. For example, I had only 16 patients with diagnosis of urinary issues as primary diagnosis and only 14 patients who experienced some/major barriers to follow medication schedule. Future studies should pay attention to gathering more information on those important variables. In addition, larger sample might contribute to improvement of the PREVENT's predictive ability.

Innovation

This dissertation study offers several methodological and practical innovations. First, the study created an easily replicable conceptual link between nursing specific theory and informatics theory (Topaz, 2013). Currently, there is an increasing attention to health informatics, both in nursing practice and research, and I hope that the merge of the frameworks developed here will help others in the field. Secondly, in the recent years, clinical decision support tools have become a standard of care and a government requirement in many inpatient settings. However, those trends have yet reached home health settings and this study is one of the first to develop a tool for these settings. Finally, PREVENTs uniquely contributes to the growing body of knowledge on health transitions and care coordination by suggesting a combination of factors that can guide first nursing home health visit prioritization for patients discharged from hospitals.

Future Plans

My future plans include further validation of the PREVENT tool with a larger patient/expert sample and experimental implementation of the tool into clinical practice of a home health agency to estimate the possible effect on short term/long term outcomes. Ideally, the experimental application should be examined in conjunction with other programs, such as targeting high priority patients for early medication reconciliation and education or an increased attention to patients with depression. This dissertation study focused on developing a tool for patients discharged from hospitals. There is a need in creating a similar tool for patients admitted from other settings (e.g. primary care). An additional venue for future exploration is development of a tool that will suggest a set of specific home health services based on a range of patient needs. For example, patients with lack of social support might benefit from early social work intervention while patients with decline in functional level might use physical therapy services. My long term goal is to gain expertise in creation of computerized tools to promote care in home health and post acute care settings and this dissertation is a first step towards achieving this goal.

Conclusion

Millions of Americans are discharged from hospitals to home health settings every year and about third of them return to hospitals within 60 days. An increasing body of evidence shows that up to 60% of those patients are rehospitalized within the first two weeks of services. One approach to reduce these high rehospitalization rates is to target services for patients who need them the most. Unfortunately, only fragmented evidence exists on factors that should be used to identify high risk patients in home health. This dissertation study aimed to bridge gaps in knowledge and to (1) identify factors associated with priority for the first nursing visit and (2) to construct and validate a decision support tool for patient prioritization. I recruited a geographically diverse convenience sample of nurses with expertise in care transitions and care coordination to identify factors supporting home health care prioritization.

A combination of data mining and logistic regression models was used to construct and validate one of the first clinical decision support tools for home health settings, the “PREVENT”- PRiority home health Visit Tool. The finalized PREVENT tool includes five factors: namely, presence of wound; number of medications; number of comorbid conditions; toileting functional status and presence of a comorbid condition of depression. My future plans include further validation of the tool and experimental application of the tool in home health practice to estimate its effect on clinical outcomes.

APPENDIX 1: Past, Present and Future: Overview of Main Trends in US Home Health

This appendix briefly reviews the past, present and future trends in the US home health services and establish the context for the specific aims of this study.

The past

The first documented home health care in the U.S. can be traced back to 1813, when the wealthy women of South Carolina's "Ladies Benevolent Society" started to visit poor patients in their homes (Buhler-Wilkerson, 2007; Murkofsky & Alston, 2009). By the turn of twentieth century, several small organized groups of wealthy women in large cities (such as New York, Boston, Philadelphia etc.) were hiring nurses to bring "care, cleanliness and character" to the sick and poor at home. The care was often provided for free. Over time, the number of similar efforts increased significantly and in 1909, almost 600 community organizations across the U.S. sponsored nurses to provide care at homes. Around this time, Lillian Wald -who coined the phrase "public health nurse" and started the Henry Street Nurses Settlement House in New York- convinced the Metropolitan Life Insurance Company to pay for home health visits (Buhler-Wilkerson, 2007; Murkofsky & Alston, 2009). In a few years, the company had extended its coverage and established the first national system of insurance for home health services.

In 1965, Medicare was signed into law as a part of Social Security Act; it included the extension of home health services for all Americans aged 65 and over regardless of income. In 1967, there were 1,753 Medicare- certified home health agencies across the U.S. and these numbers grew significantly to 2,924 by 1980 (The National Association for Home Care & Hospice, 2010). Several legislative and regulatory changes and the implementation of the Prospective Payment System -leading to a quick discharge of sicker patients from hospitals (Kosecoff 1990). This led to exponential growth of home health agencies and Medicare expenditures on home health. Between1967 and 1990, Medicare's home health spending increased by 350% and in 1997, there were 10, 444 Medicare certified home health agencies across the US (Murkofsky & Alston, 2009; The National Association for Home Care & Hospice, 2010).

The tremendous growth of home health industry awakened public reports of fraud and abuse (Murkofsky & Alston, 2009). In 1995 the federal government launched an operation called "Restore Trust" that confirmed that many Medicare expenses, including the home health services, were unnecessary or based on fraud. These events led the Congress to require that Medicare administration develop a home health prospective payment system to control the spending (under the Balanced Budget Act of 1997). The new payment system was intended to create financial incentives for more efficient care. In 1997, an Interim Payment System was implemented until the transition to prospective payment system was made in 2000. As a result, one third of the home health agencies had closed by 2001 and the eligibility criteria, constitution and the length of home health services in the U.S. have changed dramatically (MCCall, 2002).

The present

The home health sector recovered and adjusted to the recent changes in legislation and the payment system. In the past decade, the number of CMS certified agencies across the U.S. has almost doubled (11,633 agencies in 2012 vs. 6,861 agencies in 2001) (The National Association for Home Care & Hospice, 2010). The <u>overall goal</u> of today's' home health is to provide treatments for an illness or injury and to help patients regain independence and control over their health condition. For chronic conditions, home health aims to assist patients with maintaining the highest level of independent function and teach patients the required self-care skills to live with their disease (Murkofsky & Alston, 2009). When possible, providing healthcare at home is safe and less expensive than acute care or long term services. With the current advances in medical technology and pharmaceutics, many patients and healthcare stakeholders prefer care at homes over emergency room visits, hospitalizations or nursing homes (American Medical Association and American Academy of Home Care Physicians., 2007; Murkofsky & Alston, 2009).

Home health services delivery is highly influenced by the payer. Medicare is the single largest payer for home health; in 2010 Medicare covered 41% (or about 31.5 billion dollars) of home health services (Center for Medicare and Medicaid Services, 2011b). Other payers include Medicaid (24%); state and local governments (15%); out of pocket (10%); private insurance (8%); and other sources (2%) (The National Association for Home Care & Hospice, 2010). Coverage of home health services differs between the insurers: some payers (e.g. Medicaid and state and local governments) offer greater flexibility and pay for non-skilled and supportive services or may not require all patients to be homebound (Medicaid requirement). Also, there are differences in the structure of home health payments; Medicaid pays for 60-day episodes of care based on patient acuity while others (e.g. Medicaid) pay a fixed rate per-visit and often require preauthorization for each visit.

To be eligible for Medicare home health services, patients must meet the following criteria (Centers for Medicare & Medicaid Services, 2012a): (1) home care must be medically necessary and supervised by the patient’s physician; (2) care must require a registered nurse (RN), physical therapist, or speech-language pathologist; (3) nursing care must be part time or intermittent; and (4) the patient must be homebound, meaning that leaving home is a considerable and taxing effort. Patients might be absent from their homes but that should be infrequent and patient should rely on the assistance of another person or assisting device. For example, it acceptable for patients to go to a medical appointment or a church. Other absences from the home are permitted (e.g. occasional trips to the barber, a walk around the block, or a drive; attendance at a family reunion, funeral, graduation, or other unique event) as long as they are infrequent and require considerable effort (Centers for Medicare & Medicaid Services, 2012a). Care must be provided at patients' homes or other group personal care homes (such as assisted living facilities).

Under the current Medicare Prospective Payment System, home health agencies are paid a pre-set amount for each 60 days care episode, regardless of visits provided. Payments are case-mix adjusted, so the agencies receive higher payments for sicker patients. Also, there is a system of outlier payments for the most and least expensive beneficiaries (e.g. the most complex patients or patients that require less than 4 visits during the 60 days episode). Medicare covers the following services: skilled nursing care, provided by an RN or a licensed practical nurse; physical, occupational, or speech therapy; medical social work; home health aide services; and medical supplies (Centers for Medicare & Medicaid Services, 2012a). Medicare provides a bundled payment to the agency for all covered services; it will not pay for therapy or medical supplies from other providers or suppliers. Medicare also does not pay for homemaker services unrelated to the plan of care (e.g. shopping, cleaning, and laundry); personal care given by home health aides when this is the only care needed; 24-hour care at home; or meal delivery.

CMS also aims to constantly improve the quality of home health and Outcome and Assessment Information Set (OASIS) plays an important role in these efforts

(Centers for Medicare & Medicaid Services, 2005). OASIS, a standardized comprehensive assessment for adult home health patients, was constructed through 10 years of development and formal testing; it provides sociodemographic, environmental, support system, health status, and functional status data. The OASIS (currently in its third revised version, OASIS-C) serves two major purposes: it is used to 1) construct case-mix for CMS payments under the Prospective Payment System and 2) to report quality indicators to the CMS. Currently, the CMS publically reports 22 quality indicators for each of the certified home health agencies. The reports are gathered and generated by the Outcome-Based Quality Improvement, CMS's systematic approach aimed at helping home health agencies to improve their quality of care (Center for Medicare and Medicaid Services, 2010). One example of a publically reported quality measure is the adjusted rate of hospital admissions; this measure shows how often patients were admitted to the hospital while under the care of the home health team. According to the CMS, lower numbers are better for this measure, because the home health team, in many instances, can prevent the need for hospital care (Center for Medicare and Medicaid Services, 2013b).

Medicaid is yet another significant payer for home health care and it covers about one fifth of the services (Murkofsky & Alston, 2009; The National Association for Home Care & Hospice, 2010). Unlike Medicare, Medicaid is a joint state-federal program; its eligibility and benefits vary between the states. In general, it provides health coverage or nursing home coverage to certain categories of low-asset people, including children, people with disabilities, elderly needing nursing home care, etc. Under federal Medicaid rules, coverage of home health services includes skilled nursing (part-time), HHA services, and medical supplies and equipment. At the state's level, Medicaid may also cover physical, occupational, and speech therapies or medical social services. Other payers for home health services, such as state and local governments or private insurances, have diverse rules for service eligibility and provided care (Center for Medicare and Medicaid Services, 2011a).

One fundamental difference between the home health services payers concerns the scope of the addressed health problems; while Medicare aims to provide services meeting a variety of patient medical and social needs within the 60 days episode of care, other payers often focus on one specific care goal (Murkofsky & Alston, 2009). For example, a managed care plan might order skilled nursing services from a home health agency to focus on a specific care goal, such as wound treatment. However, many wound patients have comorbid conditions and would also require nutrition instruction, mobility training, incontinence assessment, or heart failure control. In this case, a task oriented approach focused on wound care only might be not effective and the home health nurses serve as vital advocates to prove the importance of additional services to meet patient unmet needs and problems. On the other hand, more flexible approach to payment for the home health services might enable longer – than CMS's 60 days-periods of care and inclusion of additional patient populations (Murkofsky & Alston, 2009). To date, there is not enough information to identify care model that results in the best possible patient outcomes.

The future

Rapid population ageing, increases in the number and severity of chronic diseases, and growing complexity of the medication regimens require healthcare researchers and stakeholders to reconsider the existing models of care (Centers for

Medicare & Medicaid Services, 2012b). It is evident that more healthcare services will be needed, especially those provided outside of the hospitals. In home health, the quantity of services was the main driver for reimbursement from 1965 to 2000. Transition to a Prospective Payment System, introduction of a quality of care and outcome measures facilitated the implementation of quality of care driven approach (Murkofsky & Alston, 2009).

Several recent legislative and regulation trends represent the transition to a more collaborative, quality oriented care model assisted by health information technology. First, the Affordable Care Act, or the Healthcare reform, encourages more home and community services in several cost-effective ways (Manchikanti et al., 2011; U.S Senate, 2011). The Act makes it easier for the states to add home health services to their Medicaid programs; in the past, states needed to renew their federal approval every three to five years. The law also makes home health available to more individuals. For example, it is suggested to expand Medicaid home health coverage for beneficiaries that have either: at least two chronic conditions (e.g. diabetes, asthma, obesity, heart disease, mental condition, and substance abuse disorder); one chronic condition and being at risk for another; or one serious and persistent mental health condition (Kaiser Family Foundation, 2011). Additionally, the law finances several ongoing demonstration projects aimed at providing better care in home settings. For instance, more than 100 Home Health Agencies are currently participating in a the two-year Medicare Home Health Pay-for-Performance demonstration. These agencies are getting $15 million in shared savings from providing better care at lower cost (Center for Medicare and Medicaid Services, 2012a).

The Affordable Care Act has also enacted several rehospitalization reduction programs. For instance, starting in October 2012, hospitals across the US are financially penalized if their patients with acute myocardial infarction, heart failure or pneumonia are rehospitalized with 30 days from hospital discharge (Center for Medicare and Medicaid Services, 2012b). The financial penalties (adjustment in payments for treating these patients) are increasing and new conditions will also be added sometime soon (Center for Medicare and Medicaid Services, 2012b; Quality Net, 2012).

Another legislative example of a changing healthcare environment is the introduction of Health Information technologies. In the US, the American Recovery and Reinvestment Act of 2009 introduced the principle of Meaningful Use (under the Health Information Technology for Economic and Clinical Health Act) (Office of Management and Budget Guidance to Federal Agencies, 2009). According to this regulation, most of the healthcare providers will have to adopt and meaningfully use Electronic Health Records by, approximately, 2020 (Office of the National Coordinator, 2012; U.S. Department of Health and Human services, 2011). There are financial incentives (eligible health providers can receive up to 48,000$ for achieving Meaningful Use) and disincentives (eligible providers who did not adopt Electronic Health Records will receive less reimbursement for care provided to the CMS patients starting from 2015) for the providers to comply with the Meaningful Use requirements. So far, the regulation had a major effect on the US healthcare information technology adoption: for instance, the proportion of physicians using an Electronic Health Records increased from 48% in 2009 to 72% in 2012 (Center for Disease Control, 2012).

One of the major goals of the Meaningful Use regulations is to improve care coordination and transitions of care through information technology. A central requirement for the health information technology systems, particularly Electronic Health Records, is to have a decision support capability. The Office of National Coordinator for Health Information Technology envisions the future American healthcare provider empowered by smart information technologies that enable the provision of better services at the point of care (Office of the National Coordinator, 2012).

The general aim of this dissertation is to address these important legislative and regulatory trends and contribute to the fast developing care coordination efforts by constructing a decision support tool that will enable better linkage and thereby facilitate the transition between inpatient and home health settings. The proposed clinical prioritization tool is also intended to help clinicians to provide individualized patient care and enable better decisions on health resource distribution at the point of care.

APPENDIX 2: Detailed Description of the Data Mining and Other Statistical Methods Implemented in this Study

Regression Models

Two types of regression models were considered for the final analysis of this study's data. The choice of the model was contingent on the study outcome distribution: if I had enough data to present the outcome as a variable with three categories of priority (low, medium and high) I could have used the ordinal logistic regression, otherwise, an alternative approach was the logistic regression. In general, logistic regression models (Long, 1997) are appropriate when dichotomous dependent variable is examined. Logistic regression which is designed to incorporate many independent variables in the least squares optimization model as predictors of the outcome. The form of the logistic function is $\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{e^{\beta_0+\beta_1 x}+1} = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}}$.

On the other hand, ordinal logistic regression models are a generalized case of logistic regression that can be applied to analyzed ordinal outcome variable (Hosmer et al., 2013). The form of the ordinal logistic function is

$$\Pr(y = m \mid \mathrm{x}) = \Pr(\tau_{m-1} \leq y^* < \tau_m \mid \mathrm{x})$$

Both of those models can incorporate many independent variables as predictors of an ordinal dependent variable (expert decision on patients' risk for immediate poor outcomes). The independent variables were the disease characteristics, medications, patient needs, social support factors and other characteristics presented in the case summaries.

Both of the models predict the probability of an observed outcome for a given value of x is the area under the curve between a pair of cutpoints. For example, the probability of observing y (in our case priority for the first visit category) = m for given values of the x's (characteristics included in the final regression model) corresponds to the region of the distribution where y falls between τ_m-1 and τ_m.

Overall fit of the ordinal logistic regression models was evaluated by examining the Hosmer-Lemeshow Goodness-of-Fit tests (Hosmer et al., 2013). This test helped verifying the assumption (or the null hypothesis) that the model adequately fits the true outcome probabilities. The statistic is constructed by categorizing the predicted probabilities into deciles (priority category) and comparing the observed and expected number of events and non-events within each category. When the model fits, the test statistic has an approximate Chi-square normal distribution.

Assessing the predictive utility for prediction equations from the regression is useful for comparing among alternative models as well as for establishing predictive power. Predictive utility is often assessed using discrimination indices (Pepe, 2004). For ordinal and logistic regressions models a useful discrimination index may be defined on the basis of the area under a Receiver Operating Characteristic Curve (AUC) (Cook, 2007; Pepe, 2004). Such an ROC curve may be constructed from model-based predicted probabilities by graphing sensitivity on the y-axis versus 1-specificity on the x-axis for a number of ordered categories. If a randomly selected case (i.e. a patient categorized into the high risk for immediate poor outcomes) and a randomly selected non-case are obtained, then the AUC estimates the probability that the case has a larger predicted probability than the non-case (Pepe, 2004). Thus, value of the AUC is an estimate for the probability of concordance between predicted probabilities and true observed decisions. A value of 0.5 indicates no predictive discrimination while values above .7 indicate fair predictive ability.

AUC calculations are often used to estimate binomial distributions but they can also be extended to estimations applicable in a case of ordinal logistic regression (nonparametric AUC analysis). In ordinal logistic regressions, the AUC analysis might be performed using "roctab" command in STATA based on the extension of the AUC analysis for multiple class data suggested by Hand & Till (2001). The AUC analysis can also be used to determine the optimal cut-point for the risk for poor outcomes (Pepe, 2004). The determination of the optimal cut-point is based on both outcome prevalence and the ratio of costs associated with false positive predictions to costs associated with false negative predictions. These costs are derived for the specific context in which the prediction is being made, including costs from the patient's perspective and costs from HHA perspective. The cut-point that minimizes total errors may be used when costs are equal or when there is no information regarding costs. In that case, the optimal cut-point is derived from the ROC curve using the ratio of one priority groupings to the others. The optimal cut-point is located where the slope of the line tangent to the curve is equal to this ratio (Hand & Till, 2001). This analysis determined the best-fit cutoff point for the risk for priority of the first home health visit decisions.

I also used a technique called forward stepwise variable selection (in STATA). In this iterative approach, multiple regression models are implemented while significant variables are added and retained in the model.

Data Mining Methods

Due to the large number of variables that were considered (n=63), I conducted several data mining analysis approaches to select variables that have high potential to affect the outcome variable of interest.

One of the techniques applied were the classification trees, a statistical technique that uses recursive partitioning to separate the subjects into priority categories (Witten et al., 2011). Classification tree learning is a method commonly used in data mining. The goal of this method is to create a model that predicts the value of a target variable based on several input variables. To accomplish that, classification trees present the dependent variable as an interior node corresponding to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf (Witten et al., 2011).

I applied standard classification algorithms J48- based on the original C4.5 algorithm developed by J. Ross Quinlan- classification trees in which variables are selected based on the information gain (the measure of the "purity" of a an association of independent variable with the outcome) (Witten et al., 2011). The classification trees helped finding the variable at each stage that best separates the subjects into the priority groups; these variables were considered for the predictive logistic regression model. Additionally, I used classification technique called Random Trees- which is an extension of the simple classification trees. In Random Tree approach, the model is constructed using K randomly chosen attributes at each node. The assumption of those models is that several decision trees models, when taken together, can produce better results that just one tree. Random Trees are available in WEKA (weka.classifiers.trees.RandomTree).

In addition, I applied the following approaches to estimate variable subset with best predictive abilities:

- Naïve Bayes- a probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions between the variables.
- Logistic regression classifier- a classification algorithm based on the application of logistic regression.
- Rules (PART classifier): a classification algorithm that assigns population elements into a specific class (e.g. priority). The results are tested based on whether elements were assigned to the class they really belong.

I also used several feature feature selection algorithms. For example, I used the correlation based CFS subset evaluator (CfsSubsetEval). This algorithm assesses the predictive ability of each independent variable individually, given the degree of redundancy among them. It prefers sets of attributes that are highly correlated with the outcome variable but have low intercorrelation. Additionally, I used a chi-square based feature selection algorithm (ChiSquaredAttributeEval) that evaluates independent variables by computing the chi-squared statistic with respect to the outcome variables. Additional methods for feature selection applied included the Information Gain and Gain Ration evaluators.

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